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Essays in Macro-Finance

submitted by

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for the degree of Doctor of Philosophy

of the

University of Bath

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October 2017

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Signed on behalf of the Faculty of Humanities and Social Sciences.....

*To my parents
and beloved Hyun Jeong and Dayeon*

Abstract

Despite the traditional separation of academic studies regarding macroeconomics and financial markets, recently, there has been increased interest in investigating the relationship between them based on models of the term structure of interest rates. This thesis in “Macro-finance” connects macroeconomic variables and the fixed income financial markets, both Treasury and corporate. Traditional economic models in linking these markets with the macroeconomy concentrate on the determination of the short rate, as the policy instrument, via the familiar Taylor-rule. The essays in this thesis provide evidence of the mutual relationships in two dimensions: a) price formation in these markets and macroeconomic conditions originating from home and abroad, and b) information originating in these markets and expectations regarding the future state of the economy.

In the first essay, we study the impact of oil price shocks in the global crude oil market on the dynamics of the entire term structure. The responses of the yield factors to oil market shocks are shown to differ contingent on the underlying sources driving oil price shocks and the country’s dependency on oil. The oil supply and demand shocks explain a considerable amount of variations in the term structure of interest rates, especially in countries with high oil dependency.

The second essay tests the predictive power of economic policy uncertainty (EPU) for future bond returns. Using the policy uncertainty measure recently developed by Baker et al. (2016), we investigate the relationship between economic uncertainty and excess bond returns. The impact of the uncertainty is shown to be larger for shorter maturities in near investment horizons. An affine term structure model incorporating the uncertainty factor produces higher fluctuations in term premia estimates which display strong countercyclical movements and accords with expectations.

Finally, we examine whether professional forecasters incorporate high-frequency information about credit conditions in revising their economic forecasts. Using Mixed Data Sampling regression approach, we find that daily credit spreads have significant predictive ability for monthly forecast revisions of output growth, at both aggregate and individual levels. The relations are shown to be notably strong during ‘bad’ economic conditions, indicating that forecasters anticipate more pronounced effects of credit tightening during economic downturns.

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Chapter 1

Introduction

Understanding the dynamic evolution of the yield curve is an important issue in finance and economics. Central bankers pay close attention to the term structure of interest rates in order to extract market participants' expectations over the future economic conditions. Investors in financial markets also closely follow the prices of fixed income securities, as they carry a large amount of information providing insights crucial for asset allocation and risk management.

Even though studies have pointed out the importance of augmenting macroeconomic perspective in asset pricing (for example, Campbell 1986), there have long been separate strands between the financial economist and macro economist in investigating the term structure of interest rates. On the one hand, financial studies for example, have mainly focused on fitting and forecasting the bond yields, but provide no clear inter-relation with macroeconomic conditions. On the other hand, macro models have considered that the rates on long-term bonds are determined by expected future short rates, without much interest within the effects of the different risk premia.

The essays in this thesis attempt to fill the gap by exploring the connect-
edness between the macroeconomy and the term structure of interest rates in a
macro-finance perspective. The first two papers investigate how macroeconomic
fundamentals explain observed dynamics in the term structure of interest rates.
The third paper studies the other direction of the relationship, examining the value
of financial information when forecasting the macroeconomy.

In the first paper, we study the impact of oil price shocks in the global crude oil
market on the dynamics of the entire yield curve in four industrialised countries;
the US, Canada, Norway, and South Korea. This is the first set of empirical
results on this topic as most of the literature has been concentrated on the impact
of these shocks on macroeconomic aggregates. We test for the sensitivity of the
latent factors describing the term structure (level, slope, and curvature), obtained
from the dynamic Nelson-Siegel model using the Kalman filter, to shocks in the
oil markets. Based on a structural VAR framework, we find that the responses
of the term structure factors to oil market shocks are different contingent on the
underlying sources that drive oil price shocks and the country's dependence on
oil. Oil market-specific demand shocks result in increases in the level factor in oil-
importing countries but have no such effect in oil-exporting countries. Oil supply
disruptions have short-lived negative responses of the slope factors in the US and
Canada, associated with loosening monetary policy, whilst demand side shocks
tend to lead to increase the slope in all countries. Overall, oil supply and demand
shocks jointly account for a considerable amount of the observed variation in the
term structure of interest rates, explaining up to half of the changes of the yield
factors in countries with high oil dependency.

The objective of the second chapter is to find macroeconomic factors explain-
ing the risk premia embedded in long-term bonds, rather than extending the set of

principal components with limited economic interpretation. Specifically, we study the forecasting power of economic uncertainty in government policies (EPU) for future bond returns. Using the policy uncertainty measure developed by Baker et al. (2016), we investigate the relationship between economic policy uncertainty and bond returns. Return forecasting exercises confirm that this uncertainty factor predicts bond excess returns, even when controlling for the well-established return forecasting factors, and that the predictive ability is especially large for shorter maturities in near investment horizons. Estimating an affine term structure model for the US, we find that term premia estimates implied by the model with this additional risk factor, instead of additional principal components, exhibit time-varying and countercyclical movements, providing an economically meaningful explanation for the required higher risk compensation under adverse economic conditions as expected by theory.

In the third paper, we examine whether professional forecasters incorporate high-frequency information, from the financial markets, specifically about credit conditions, in revising their economic forecasts for GDP growth. The study on the effects of credit conditions on economic activities has acquired increased relevance since the recent financial crisis, as traditional macroeconomic models did not take into account that developments in financial markets are amplifying the impact of macroeconomic shocks. More specifically, we examine whether current developments in corporate credit markets influence professional forecasters' predictions for future output. Using Mixed Data Sampling (MIDAS) regression approach, we show that increases in daily credit spreads, measured as the difference between the rates of long-term Aaa-rated corporate bonds and 10-year Treasury, forecast significant downward revisions at both aggregate and individual forecast levels. The effect of the credit spreads is found to be particularly strong during 'bad' economic

conditions, suggesting that forecasters consider that the effects of credit tightening become more pronounced during economic downturns, indicating the amplification effect of financial developments on macroeconomic aggregates.

Chapter 2

The Impact of Oil Price Shocks on the Term Structure of Interest Rates

2.1 Introduction

Oil prices are considered as one of the main drivers of business cycle fluctuations. Since the sequential oil price shocks during the early and late 1970s, the impact of oil shocks on macroeconomic activity has been investigated by many empirical studies. Literature initiated by Hamilton (1983) has focused almost exclusively on the relationship between changes in the price of oil and economic activities, revealing a significant negative impact of oil price hikes on GDP growth (see, Hamilton 1985, 1996, 2009; Rotemberg and Woodford 1996). Attention has also been given to the role of oil prices in determining inflation (Hooker 2002) and inflation expectations (Harris et al. 2009; Coibion and Gorodnichenko 2015b), and

more recently their declining pass-through into inflation and economic activities (Blanchard and Gali 2007; Chen 2009; Clark and Terry 2010; Baumeister and Peersman 2013).

Even though much literature has studied the macroeconomic influences of oil price shocks, research on the relationship between oil prices and financial market variables has been limited and related studies (for example, Chen et al. 1986; Huang et al. 1996; Kilian and Park 2009) have mainly focused on the effects of oil shocks on stock returns. In comparison, little attention has been paid to the effect of oil prices changes on the bond market. Literature which considers the response of interest rates to oil price shocks has focused on the short-end of the yield curve, in an attempt to quantify the contribution of monetary policy responses to the propagation of oil price shocks (see, for example, Bernanke et al. 1997).

This paper attempts to fill this gap by incorporating the term structure factors and variables driving supply and demand in global crude oil markets into a structural VAR (SVAR) model. In this context, we examine the effects of oil price shocks on the term structure of interest rates. Furthermore, to consider the different dynamics between oil shocks and the yield curve in oil-importing and oil-exporting economies, we study four industrialised countries with distinct positions in global oil market; the US, Canada, Norway, and South Korea.

More specifically, we examine the effects of three different oil shocks in the spirit of Kilian (2009)'s "Not all oil price shocks are alike." To relate the supply and demand oil shocks with the term structure of interest rates, we use the well established framework from the finance literature which summarises the entire term structure into several latent yield factors - level, slope, and curvature as the only relevant factors to characterise the yield curve (see, for example Litterman

and Scheinkman 1991). The factor model of the term structure combined with the decomposition of oil price shocks, into different causes, enable us to characterise the responses of the yield curve to various shocks and to calculate the entire yield curve movement after them. To our knowledge, this is the first paper answering this question, linking oil price shocks to the term structure of interest rates.

Our contribution to the literature is threefold. First, we examine the effects of oil price shocks on the entire yield curve, rather than limiting our focus on a particular interest rate, for example, short-term policy rate. To interpret the response of the latent yield factors, we follow the methodology of recent macro-finance literature which studies the macroeconomic forces that shape the term structure of interest rates (Ang and Piazzesi 2003; Diebold et al. 2006). Second, we estimate the different dynamic effects on the yield curve due to three demand and supply oil price shocks from distinct underlying sources. Third, we estimate the model using the term structures of four industrialised countries to establish whether the pattern of term structure responses to the oil price shocks is different according to their position in the crude oil market.

To ascertain the empirical robustness of our results we undertake the analysis over two periods, guided by the behaviour of the short-run rate of interest. From the onset of the financial crisis, central banks have taken drastic steps in reducing the monetary policy instrument to near zero and kept it as low for an unprecedented lengthy period. In addition, the introduction of quantitative easing in the US and UK has exercised strong downward pressure on the long-term rates altering the slope of the yield curve. In the light of such changes, we conduct our analysis over two periods. The sub-sample period ends in 2008, the onset of the crisis, where short-term rates were at their ‘historically’ normal levels. Our full sample period includes the period of the crisis and the exercise of unconventional monetary policy.

The differences in responses, if any, between the ‘normal’ and ‘extended’ periods will be due to the unusual behaviour of the short-term rate and quantitative easing. This approach helps us establish the severity of the impact of oil shocks of any description in normal and crisis times.

Our estimation results show that the responses of the four countries’ term structure are not alike, depending upon the type of shocks and the countries’ position in the crude oil market. Broadly speaking, the response of the factors of the yield curve to the different sources of oil market shocks can be summarised as follows: The impulse response analysis shows that negative oil supply shocks have differential effects on the level (long-end), with rising levels in Norway and South Korea and little effect on US and Canada; in these two countries the shock results in lower short rates, steepening the yield curve. This result is associated with the conventional monetary policy reaction aiming at offsetting the recessionary effects of oil supply disruption. Following an oil market-specific demand shocks, the level of the yield curve in oil-importing countries (the US and South Korea) increases noticeably, but the response of the same factor in oil-exporting countries (Canada and Norway) is very modest.

In all countries, the slope increases after oil market-specific demand shocks following a rise of the short rate, which is the consequence of the monetary policy’s reaction to reduce inflationary pressures. Finally, aggregate demand shocks make the slope factor in oil-importing countries less steep, but have no such effect in oil-exporting countries. The same shocks decrease the curvature (middle-end) of the yield curve in oil-importing countries making yield curve less concave.

The rest of the paper is organised as follows: a brief literature review is presented in Section 2. Section 3 presents the Nelson-Siegel methodology and the

SVAR model. Section 4 provides a description of the data. Section 5 discusses empirical results and comments on the dynamics of the term structure responses to oil shocks. Finally, Section 6 concludes.

2.2 Literature Review

Finance literature models treat nominal yields as functions of several unobservable factors. Imposing the no-arbitrage condition, yields of various maturities acquire consistent dynamic evolution according to underlying factors (Duffie and Kan 1996; Dai and Singleton 2002). However, these canonical arbitrage-free term structure models have not provided much intuition regarding the macroeconomic forces that drive the underlying yield factors. The empirical literature has attempted to include macro variables and builds macro-structures into financial term structure models to incorporate the fundamental macroeconomic drivers of the yield curve.

In a seminal work by Ang and Piazzesi (2003), the combination of macroeconomic and latent yield factors results in a state vector whose dynamics follow a first order Gaussian VAR. As macro variables, they use principal components of the series that represent inflation and output measures. The short rate is assumed to be an affine function of the state variables. With the aid of no-arbitrage assumption, yields with various maturities become affine functions of the state variables which include both financial and macro factors. They conclude that macro factors explain significant of variations of bond yields and the model incorporating macro factors forecasts better in comparison to a model relying exclusively on financial factors.

The initial macro-finance models have included a limited number of macroeco-

conomic aggregates such as output and inflation. Based on the tradition of Taylor (1993), these have focused on using information about output and inflation as determinants of the movements of the short-term rate. As reported in Ang and Piazzesi (2003), the shocks from these macroeconomic factors do not have sufficient explanatory power to account for interest rate movements with longer maturities.

Subsequently, a large number of empirical studies have followed and established the relationship between macroeconomic variables and the term structure of interest rates. They consider different structures in factor dynamics or introduce additional latent and macro factors.¹ For example, Diebold and Li (2006) and Ang et al. (2007) allowed for feedback between macro and yield factors in the dynamics of the state variables in a bidirectional way.² Rudebusch and Wu (2008) exploit this approach³ and attempt to interpret the evolution of the latent factors in terms of macroeconomic variables. In particular, the first factor, associated with level in the yield curve, is interpreted as an interim or medium-term inflation target and the slope factor is linked to the central bank's policy responses to stabilise output and inflation fluctuations. Their empirical results conclude that the macroeconomic factors are closely related to the financial latent factors driving the yield curve.

Another strand of macro-finance literature uses a dynamic factor model which is originated from the term structure model of Nelson and Siegel (1987). For example, Diebold and Li (2006) reinterpret the Nelson-Siegel representation as a dynamic

¹This kind of research includes, for example, Bernanke et al. (2004), Dewachter and Lyrio (2006), Ang et al. (2006), and Lildholdt et al. (2007).

²The model of Diebold and Li (2006) is rooted on Nelson and Siegel (1987), but Ang et al. (2007) build their model under the no-arbitrage assumption.

³Other models with this strand include Hördahl et al. (2006) and Rudebusch et al. (2006). More recently, literature such as Bekaert et al. (2010) and Hördahl et al. (2008) extend the existing model in a way that allows more fully specified structural DSGE model.

latent factor model. The advantage of the Nelson-Siegel type model is that it is free from the estimation problems of the canonical affine no-arbitrage term structure models that suffer from empirical performance in terms of fit and out-of-sample predictability (Duffee 2002) due to its parsimonious framework. Diebold and Li's simplified model where factor dynamics are assumed to follow a first-order vector auto-regression has been used for forecasting purposes with some success.

To improve the performance of the original models and establish explicit links with the macroeconomic environment, additional macroeconomic factors have been added to account for the observed movements of the yield curve. Dai and Philippon (2005) using affine structures, and Afonso and Martins (2012) using the econometric approach of Diebold and Li (2006) incorporate additional elements representing fiscal conditions such as the government deficit. They argue that fiscal shocks indeed affect long-term rates through the expectations of the future short-term rate as well as the risk premium. Chadha and Waters (2014) consider a large number of macroeconomic variables into a macro-finance model and Dewachter and Iania (2012) introduce two additional financial factors, liquidity-related and return-forecasting factors. The liquidity-related factor is a measure of money market tension, whilst the return-forecasting is a factor driving the one period expected excess holding return. They found that the model fit with the two financial factors is enhanced, and that the additional factors have a significant influence on the yield curve.

Even though the macro-finance literature has largely investigated the possible role of macroeconomic factors in the dynamics of the term structure, studies on the effect of oil price shocks on the term structure are relatively limited. The literature has been mostly focused on only the short-end of the yield curve, with the aim of evaluating the possible role of monetary policy response in the propagation of oil

price shocks. Using US data in a VAR model, Bernanke et al. (1997) investigate endogenous monetary policy response to oil price shocks in an attempt to investigate whether it is the cause of past economic downturns which followed after them. They concluded that the systematic response to oil price shocks is indeed the main reason for these recessions and that different monetary policy could have been used to avoid their recessionary consequences.

Their argument is challenged by Hamilton and Herrera (2004) who show that the counter-factual paths of the policy rates assumed to eliminate the output decline are implausible and cannot be implemented. They also show that when alternative lag lengths were used in the estimation of the VAR these altered the size of the effect attributed to oil shocks. Kilian and Lewis (2011) re-validate this result: that there is no credible evidence that monetary policy responses in the 1970s and 1980s amplified the effects of oil price shocks causing significant fluctuations in real output. They argue that the monetary policy reaction framework in Bernanke et al. (1997) and other following studies have a weakness in the way that they assume policy makers respond regardless of their underlying sources.⁴

Kilian (2009) considers whether distinct oil price shocks driven by diverse underlying determinants have differential effects on the economy. He classifies three kinds of shocks: shocks to the reduction in oil supply, shocks driven by increased overall demand, and shocks from the changes in the precautionary oil demand. Using a structural VAR model with recursive restrictions, he identifies oil price shocks and allocates them into the three categories. Estimation results show that historical oil price changes have been associated with a combination of all three

⁴Cognigni and Manera (2008) have studied endogenous monetary policy response to oil price shocks for the G-7 countries. Their simulation exercises using SVAR model suggest that the effects of the oil price shocks in the US is largely due to the monetary policy reactions, but for other countries such as Canada, France, and Italy the total impact is offset partly by monetary easing.

types of shocks. What is of interest is that, after the decomposition, it emerges that certain oil price shocks are connected to demand-side, a finding that is inconsistent with the common belief that oil price shocks are mostly concerned to supply disruptions and these have been the main cause of oil price fluctuations. He also finds distinct effects of each shock on output growth and inflation. For example, a shock originating from supply disruption causes an immediate but temporary drop in current output associated with trivial effects on inflation. Whilst, a shock caused by an increase in global aggregate oil demand results in a delayed and pronounced fall in output and increased inflation.

To our knowledge there is no structural model embedding the impact of oil price shocks on the term structure. However, there is strong empirical evidence of their influence of inflation expectations and subsequently on both the short and long rates. More specifically in terms of the short rate (Coibion and Gorodnichenko 2012) provide evidence that the FOMC in setting the policy rate take into account oil price shocks and Elliot et al. (2015) from the Bank of England show that even the expected 5-year inflation 5 years from now (5y5y inflation expectation) is influenced by current oil price movements.⁵ In the light of the existing empirical evidence that both ends of the yield curve are influenced by oil price shocks the aim of this investigation is to calculate the the impact of such shocks on the entity of the yield curve as represented by its essential elements.

⁵In their regression exercises, a 10% increase in daily oil price has shown to cause around 4 basis points in the US 5y5y and 2 basis points in Euro area 5y5y inflation expectation.

2.3 Methodology

We use the conventional macro-finance framework to establish the nature of the relationship between oil price shocks and the term structure of interest rates. Since Litterman and Scheinkman (1991), finance literature summarises the term structure of interest rates into three latent factors, representing level, slope, and curvature of the yield curve. In general, these three factors can explain more than 99% of the entire movement in the term structure. To extract three latent yield factors, we follow the approach of Diebold et al. (2006) who modify the Nelson and Siegel (1987)'s parsimonious exponential function form with time-varying parameters in state space setting. Unlike typical finance term structure model restricted with the no-arbitrage condition, the Nelson-Siegel model does not impose the no-arbitrage condition (Björk and Christensen 1999; Filipović 1999).

Our choice of model is based on the argument of Diebold and Rudebusch (2013) that the imposition of the no-arbitrage restriction is not necessarily important when the bond market is deep and liquid enough that its pricing satisfies the arbitrage free conditions. Coroneo et al. (2011) document that the Nelson-Siegel yield curve model is compatible with the models imposing no-arbitrage constraints in the case of US yield curve. Diebold and Li (2006) show that the parsimony but flexible functional form of the model enhances the empirical fit and results in good forecasting performance.

The estimation of the state-space yield curve and the analysis of macro-finance VAR approach follows two steps. First, we estimate the country-specific three latent yield factors using the Kalman filter, as Diebold et al. (2006). Second, we estimate SVARs with each country's three latent yield factors and variables which enable to identify the supply and demand shocks in the global crude oil market.

This procedure is similar to empirical methodology employed by Afonso and Martins (2012) who examine the effect of fiscal behaviour on the term structure of interest rates. They argue that the yield curve factors estimated using an integrated model with both macro and yield curve data do not differ much from ones attainable with the pure financial state-space model. Furthermore, this approach enables us to circumvent the restriction of the first-order specification, which is usually assumed in the finance literature.⁶ Using this methodology, we report the estimated latent yield factors and analyse the effects of the three different oil shocks on yield curve dynamics.

2.3.1 Term Structure Factor Model Representation

The conventional Nelson-Siegel model (1987) has the following functional form:

$$y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + \beta_3 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right), \quad (2.1)$$

which can be understood as a cross-sectional representation for fixed t . Figure (2-1) shows the factor loading on each latent yield factor fixing the value of λ at 0.0609 as assumed in Diebold and Li (2006). The loading on β_2 begins at 1 and decays as the maturity increases, so it is interpreted as a short-term factor. The loading on β_3 starts at 0, increases until the maturity reaches around 24 months, and decays to zero, so it can be interpreted as a medium-term factor. Finally the loading for β_1 is 1, so it is interpreted as the long-term factor. According to their effect on the overall yield curve, the three factors can be interpreted as the level, slope, and

⁶Empirical studies investigating the transmission of oil price shocks usually selects a large number of lags to capture the delayed effect of oil price shocks on the economy. Hamilton and Herrera (2004) discuss that the importance of choosing a lag length and show that the number of lags is needed to be large enough, suggesting less than 12 lags can fail to ensure the reliability of the impulse response estimates.

curvature in a conventional yield curve model. Diebold et al. (2006) show that the estimated factors mimic closely their empirical proxies for level ($y_t(120)$), slope ($y_t(3) - y_t(120)$), and curvature ($2 \times y_t(24) - (y_t(3) + y_t(120))$), where the values in parenthesis indicate the months to maturity.

To extend Nelson-Siegel's framework to represent entire yield curve, Diebold and Li (2006) consider β_i 's as time-varying yield factors with factor loadings 1, $(1 - e^{-\lambda\tau})/\lambda\tau$, $(1 - e^{-\lambda\tau})/\lambda\tau - e^{-\lambda\tau}$. Then we can rewrite Equation (2.1) to relate the β coefficients to the factors' interpretation as level, slope, and curvature as

$$y_t(\tau) = l_t + s_t \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + c_t \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right), \quad (2.2)$$

where $t = 1, \dots, T$ and $\tau = 1, \dots, N$.

The dynamic movement of the three factors (l_t, s_t, c_t) is assumed to follow a first-order VAR which becomes the transition equation controlling the dynamics of the state vector as

$$\begin{pmatrix} l_t - \mu_l \\ s_t - \mu_s \\ c_t - \mu_c \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} l_{t-1} - \mu_l \\ s_{t-1} - \mu_s \\ c_{t-1} - \mu_c \end{pmatrix} + \begin{pmatrix} \eta_t(l) \\ \eta_t(s) \\ \eta_t(c) \end{pmatrix}, \quad (2.3)$$

where μ_l , μ_s , and μ_c are mean values and $\eta_t(l)$, $\eta_t(s)$, and $\eta_t(c)$ are innovations for the respective factors. The measurement equation which relates yields with N

maturities to the three latent factors is

$$\begin{pmatrix} y_t(\tau_1) \\ y_t(\tau_2) \\ \vdots \\ y_t(\tau_N) \end{pmatrix} = \begin{pmatrix} 1 & \frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} & \frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} - e^{-\tau_1\lambda} \\ 1 & \frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} & \frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} - e^{-\tau_2\lambda} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\tau_N\lambda}}{\tau_N\lambda} & \frac{1-e^{-\tau_N\lambda}}{\tau_N\lambda} - e^{-\tau_N\lambda} \end{pmatrix} \begin{pmatrix} l_t \\ s_t \\ c_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t(\tau_1) \\ \varepsilon_t(\tau_2) \\ \vdots \\ \varepsilon_t(\tau_N) \end{pmatrix}, \quad (2.4)$$

where $t = 1, \dots, T$, and $\varepsilon_t(\tau_1), \varepsilon_t(\tau_2), \dots, \varepsilon_t(\tau_N)$ are measurement errors. We can rewrite this state-space system in a matrix form as

$$(f_t - \mu) = A(f_{t-1} - \mu) + \eta_t \quad (2.5)$$

$$y_t(\tau) = \Lambda f_t + \varepsilon_t(\tau). \quad (2.6)$$

where $f_t = (l_t \ s_t \ c_t)'$, $\mu = (\mu_l \ \mu_s \ \mu_c)'$, and $\eta_t = (\eta_t(l) \ \eta_t(s) \ \eta_t(c))'$. A is 3×3 matrix in the transition equation, and Λ is a factor loading matrix which connects the factors to the interest rates vector $y_t(\tau)$ with maturities $\tau_1, \tau_2, \dots, \tau_N$. The factor loadings are functions of maturities and determine the dynamics of $y_t(\tau)$.

We assume that the covariance matrix of the system is block diagonal as the measurement and transition innovations are uncorrelated to each other and to the initial state such that

$$\begin{pmatrix} \eta_t \\ \varepsilon_t \end{pmatrix} \sim WN\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Q & 0 \\ 0 & H \end{pmatrix}\right), \quad (2.7)$$

$$E(f_0 \eta_t') = 0, \quad (2.8)$$

$$E(f_0 \varepsilon_t') = 0. \quad (2.9)$$

The factor disturbances (η_t) are allowed to be correlated, whilst the disturbances

of measurement equation are assumed *i.i.d.*, resulting in a diagonal covariance matrix (H) as is standard in the literature. The diagonal covariance matrix of the yield measurement equation means that the deviations of observed rates from the estimated yield curve are not correlated. The conditions of Equations (2.8) and (2.9) ensure the optimality of the Kalman filter delivering maximum-likelihood estimates and subsequently optimal smoothed estimates of the latent factors.

2.3.2 Identifying Oil Price Shocks

Even though crude oil prices are driven by distinct oil demand and supply changes related closely to the global economic conditions, the price of crude oil has long been regarded as an exogenous shock to any domestic economy. However, oil price fluctuations emanating from diverse sources can have different macroeconomic consequences. The different effects of oil price shocks with distinct underlying source have received much attention in recent literature. Kilian (2009) stresses that oil price shocks have different dynamic effects on macroeconomic aggregates depending on their underlying sources.

The two consecutive oil crises, manifested by sharp price increases, in the early and late 1970s were originated from supply disruptions in the Middle East and have been widely believed to be related to stagnant growth and price inflation. Kilian (2009) argues that similar oil price increases driven by growing global aggregate demand, instead of supply disruptions, will manifest themselves in higher output and inflation, in contrast to the stagflation normally associated with the same phenomenon. Interest rates with diverse maturities might react differently to the oil price shocks with various sources. For example, if the oil price increase originates from oil supply disruption, the effect from higher expected inflation will be partly

offset by its stagnant effect on the real economy. On the contrary, if oil price increases due to global aggregate demand, overall interest rates in oil importing countries would result in temporary increases reflecting expectations over inflation and economic growth in the future.

A structural VAR model is used to examine the relationship between oil price shocks and the term structure of interest rates. We separate three oil price shocks - global oil supply, global aggregate demand, and oil market-specific demand shocks - and examine their effect on the three yield latent factors. We use following p-order standard SVAR model:

$$A_0 x_t = c + \sum_{j=1}^p A_j x_{t-j} + \varepsilon_t, \quad (2.10)$$

where x_t represents a vector of endogenous variables $(\Delta prod_t \text{ } rea_t \text{ } rpo_t \text{ } l_t \text{ } s_t \text{ } c_t)'$. $\Delta prod_t$ denotes the percent change in global crude oil production, rea_t is the index of real economic activity built by Kilian (2009), and rpo_t is real price of oil. A_0 is the contemporaneous coefficient matrix, A_j denotes the auto-regressive coefficient matrices, c is a vector of constants, and ε_t is the vector of serially uncorrelated structural disturbances.

The system relies on the simple contemporary recursive restrictions. Using the Cholesky triangular factorization, i.e. A_0^{-1} has a recursive structure, the reduced form errors ($e_t = A_0^{-1} \varepsilon_t$) are linear combinations of the structural errors (ε_t) as,

$$e_t = \begin{pmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \\ e_t^l \\ e_t^s \\ e_t^c \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil\ specific-demand\ shock} \\ \varepsilon_t^{level\ shock} \\ \varepsilon_t^{slope\ shock} \\ \varepsilon_t^{curvature\ shock} \end{pmatrix}. \quad (2.11)$$

The rationale for identification is motivated by Kilian (2009), Kilian and Vega (2011), and Afonso and Martins (2012). Specifically, oil supply shocks are all shocks that affect oil production ($\Delta prod_t$) within a month, based on the fact that oil production cannot be adjusted in a short period. Aggregate demand shocks are other shocks affecting the demand for industrial commodities (rea_t), approximating global real economic activity within a month. Oil market-specific demand shocks are all the other shocks which affect the real price of oil (rpo_t) and are related to the precautionary demand for oil.⁷

We assume country-specific financial variables, i.e. the three latent term structure factors (l_t , s_t , and c_t) are affected instantaneously by oil price shocks, but variables of global crude oil market are not affected contemporaneously by the domestic yield factors. Kilian and Vega (2011) test whether energy prices respond instantaneously to US domestic macroeconomic news at daily and monthly horizons. They find no evidence of systematic feedback from macroeconomic news to energy prices, which support the identifying restriction in the model that as-

⁷In recent study, Baumeister and Hamilton (2015) propose a less restrictive identification strategy using Bayesian formulation. They reveal that traditional approaches to SVAR models by Kilian (2009) and Kilian and Murphy (2014) can be understood as a special cases of Bayesian inferences with strong prior assumptions. However, they confirm that the model with relaxed prior beliefs produces core implications similar to those in previous studies.

sumes no contemporaneous effect from country-specific macroeconomic and finance shocks.⁸

In constructing the SVAR, the choice of lag length is an important consideration. Hamilton (2003) allows four lags in quarters to test for the nonlinear relation between oil price changes and GDP growth using quarterly data. Related literature typically reports the effects of oil price shocks on macroeconomic variables peak after three to four quarters (Kilian 2008 among many others). In a more recent paper, Kilian (2009) allows for 24 monthly lags. We choose 12 lags because the series of monthly interest rates are not long enough to produce reliable decompositions for the four countries in this study. This choice can also be justified considering a potentially long delay of the effects on the term structure from structural oil price shocks.⁹

2.4 Data

The data representing global oil supply and the status of global demand are available from 1973 on a monthly basis. The data for oil supply is world crude oil production and is provided by EIA (US Energy Information Administration). A monthly index representing demand for industrial commodities is used to proxy global real economic activity.¹⁰ The real price of oil is the refiner acquisition cost

⁸Three oil price shocks identified in our six-variable VAR model are highly correlated with those identified with Kilian (2009)'s model with correlation coefficients for the US are 0.85 (oil supply shocks), 0.90 (aggregate demand shocks), and 0.92 (oil market-specific demand shocks). For the other countries, the relations are less close due to shorter sample period. However, we confirm that all the correlation coefficients between the shocks identified by the two models are above 0.72 in any case.

⁹Estimation with 24 lags for the US and Canada, however, gives qualitatively similar results.

¹⁰This index is proposed in Kilian (2009). The extended series can be retrieved from Kilian's website (<http://www-personal.umich.edu/~lkilian/paperlinks.html>). The index is based on freight

of imported crude oil provided by the US Department of Energy and is deflated by the US CPI available from FRED (Federal Reserve Economic Data) by Federal Reserve Bank of St. Louis.¹¹

Nominal interest rates data for the US, Canada, Norway, and South Korea are used representing countries with different compositions in oil production and consumption. The US and South Korea are classified as oil importing countries, and Norway and Canada represent oil exporting countries. Each country has kept its position as a net oil exporter or oil importer during the whole estimation period. Figure 2-2 shows the status of the countries' dependencies and intensities of oil.¹² Norway marked the lowest energy dependency (-485.9%, net energy imports divided by total energy usage) among OECD countries (18.5% on average) whilst South Korea, is among countries with the highest dependency (83.5%). Total trade volume compared to GDP of the US is 29.9%, so it represents large closed economy. The others can be classified as small open economies and their trade volumes are larger than 60% of GDP (as of 2013, OECD National Accounts data).

The US Treasury yield curve is obtained from the updated data-set built by Gürkaynak et al. (2007) on the Federal Reserve website and Canadian yield curve for zero-coupon bonds are provided by Bank of Canada. The Norwegian yield curve is from Wright (2011) and updated using data from Norges Bank. Government zero-coupon rates for South Korea are provided by Korea Asset Pricing.

rates for dry bulk cargoes deflated by US CPI. The main advantage of this index representing global economic activity is that it does not require summarising procedure using exchange-rate weighting. It is also free from shifting country weights covering the demand from global markets, which is typically not satisfied by alternative measures such as the OECD industrial production.

¹¹The series since 1974:1 is provided by the US Department of Energy and extended backwards in Kilian (2009).

¹²Energy dependency is net energy imports divided by energy usage as of 2013. Net energy imports are estimated by IEA (International Energy Agency) as energy use less production, both measured in oil equivalents. The oil intensity is the ratio of oil consumption (Mtoes) over gross domestic product measured in constant US dollar at market exchange rates as of 2014.

As the available maturities of the yield curves are different among countries, we build yield curves with 17 maturities for each country using Svensson (1994)'s methodology and extract three latent term structure factors. Figure (2-3) plots end-of-month bond yields at 17 maturities ranging from 3 months to 10 years for the four countries.

The estimation periods by country vary due to data limitations for government zero coupon rates. For the US, the longest estimation period for the SVAR model is from January 1973 to December 2015. For the other countries, the estimation periods are: Canada (January 1986 to December 2015), Norway (January 1998 to December 2015), and South Korea (January 2001 to December 2015).

Table (2.1) presents the descriptive statistics of the interest rates of selective maturities and the empirical level, slope, and curvature of the yield curves for the four countries, across the whole and reduced periods. Over the crisis periods, rates for all maturities have fallen to unusually low levels by any historical reference. Since the onset of the financial crisis the slope of the yield curve in all countries decreased steepening the curve, as the sharp fall of the short rates was not followed by corresponding proportional falls of the long rates.

In the light of such important differences of the behaviour of interest rates, we undertake the study of the impact of oil shocks on the yield over two periods for the US and Canada. The whole sample period covering all the available data for both countries and the shorter pre-crisis period when short-term interest rates were 'historically normal', up to December 2008. This distinction will allow for the study of the impact of oil shocks during 'normal periods', a situation more likely to occur in the future as monetary policy reverts to its usual standard, and compare them to a period characterised by both 'normality' and rates at the zero-bounds

accompanied by the exercise of unconventional monetary policy.¹³

2.5 Empirical Results

2.5.1 Term Structure Factors

We first present the estimation results for yield curve latent factors for the four countries with their empirical counterparts defined earlier. Figure (2-4) shows the estimated factors using maximum-likelihood estimation with Kalman filter. The estimated value for λ is different amongst the four countries (US 0.0393, Canada 0.0672, Norway 0.0695, and South Korea 0.0522). The higher the value of λ is indicative that the curvature factor reaches its maximum value at the shorter maturity, and that the loading on the slope factor decays relatively faster across maturities.

The estimated factors move closely together with their empirical proxies as in related literature (for example, Diebold et al. 2006). The level moves most persistently with least variation, whereas the curvature exhibits the higher volatility. Our estimate of the level of the US yield curve is high during prominent inflation episodes in 1979 and 1982; subsequently the level has shown decreasing trend. For all the countries in the sample, the same pattern is apparent regarding the evolution of the level. In fact, the correlation between the level factor and actual monthly CPI inflation is quite high (US 0.53, Canada 0.52, Norway 0.20, and South Korea 0.49), confirming the close relationship between level and infla-

¹³Bodenstein et al. (2013) demonstrate that the propagation of oil price shocks are different when policy rates are at the zero lower bound. Specifically, when policy rates are at the zero lower bound, inflation caused by oil price shocks can lower real rates, stimulating economic activities and offsetting the usual contractionary effects.

tion. Recent macro-finance literature interprets the level factor as representing the medium-term inflation expectations (Ang and Piazzesi 2003 among many others)¹⁴ or market participants' view of the underlying medium-term inflation target of the central bank (Rudebusch and Wu 2008). The slope for each country is negative in most periods implying that on average yields increase along maturities. For any given estimated loadings, higher values of the slope factor (i.e. less steep or sometimes inverted yield curve) are associated with high values of the curvature factor a finding also reported by Afonso and Martins (2012). The estimated curvature moves closely with its empirical proxy (mid-term rate minus the average of short-term and long-term rate), with high correlation ranging from 0.68 (US) to 0.96 (Norway). The spread of the yield curve (gap between long-term and short-term rates) has long been demonstrated to have some predictive power for economic growth and recessions (Harvey 1988; Stock and Watson 1989; Estrella and Hardouvelis 1991; Ioannidis and Peel 2003), which establishes the factor's close relationship to real economic activity. The patterns of association between slope and curvature, discussed above, provide support for the argument of Mönch (2012) that increases of the curvature precede a flattening of the yield curve, which is followed by a significant decline of output.

¹⁴The Federal Reserve Bank of Cleveland and the Federal Reserve Bank of Philadelphia provide measures of inflation expectation in the US. The correlations between the estimated level factors based on the model and the ten-year expected inflation estimates by the banks are 0.93 (FRB Cleveland, between 1982:01 and 2015:12) and 0.33 (FRB Philadelphia, between 1998:01 and 2015:12).

2.5.2 VAR Analysis - Impulse Responses (Full Sample)

In this section, we report the responses of the latent factors characterising the yield curve to three different oil price shocks, using the whole sample period ending at December 2015, which includes the epoch of the financial crisis resulting in the exceptional behaviour of the short rate of interest since late 2008. The shocks are normalised to represent one-standard deviation of the innovation and are designed to represent an initial increase in the real price of oil imitating either a negative supply or a positive demand shock.

Oil Supply Disruption

The first column of Figure (2-5) shows impulse response of three latent yield curve factors of the four countries to sudden oil supply disruption. Solid lines represent impulse response functions to the oil price shocks, and dashed lines are one standard error bands computed using recursive-design wild bootstrap proposed Gonçalves and Kilian (2004) with 2,000 replications. Shocks due an unexpected oil supply disruption cause an instantaneous increase of the level factor in Canada, Norway and South Korea. Although these effects do not persist long for Canada and Norway, they do persist in the case of South Korea. In the US there is no response of the level factor to the shocks. This finding regarding the US level is consistent with Kilian (2009)'s as he also found that the impact of oil supply shocks on the overall price and subsequently to inflation is limited.

The temporary increase of term structure levels in oil exporting countries (Canada and Norway) is in line with the results of Charnavoki and Dolado (2014) and Korhonen and Ledyeva (2010), where shocks which increase commodity prices

can have a favourable effect on the economy. The increase of interest rates level is prominent in South Korea, peaking around 12 months following a negative oil supply shock. This pronounced and persisting response in South Korea may be related to its high dependency on crude oil, leading to greater concerns about future inflation compared to other countries. This result is in line with Baumeister et al. (2010) who found that countries with higher oil dependency suffer more from consumer prices increases following an oil shock, whereas inflationary pressures in net energy-exporting countries are negligible.

Slopes initially decrease after oil supply shocks in both the US and Canada. This response is consistent with the central bank's reaction, lowering the policy rate, to offset possible negative effects on economic activity from oil supply disruption. On the contrary, the decreases in slope factors of Norway and South Korea are negligible and even begin increasing after a year. We interpret this result in the case of Norway as follows: the oil price increase following an oil supply shock acts as stimulating effect when crude oil constitutes large share of exports. The response of slope factor to the same shock in South Korea can be explained by the policy reaction, increasing the short rate, to reduce the inflationary pressure possibly associated with its high energy intensity and dependency.

Curvatures of Norway and South Korea increase after oil supply shocks and persist longer in South Korea. This result may be understood by construing oil supply shocks leading to short-lived inflation uncertainty in these countries, affecting the risk premium of medium-term bonds delivering higher yield.¹⁵

¹⁵The macroeconomic content of term structure curvature is under-explored. Diebold et al. (2006) report the effect of curvature surprises on macroeconomic variables is negligible. Empirical evidence by Evans and Marshall (2007) shows that the curvature is not largely affected by various macroeconomic shocks. However, Mönch (2012) argues that surprises in curvature are followed by slope increases, announcing a deterioration of output growth more than a year ahead.

Aggregate Demand Shocks

The responses of estimated yield factors to aggregate demand shocks are shown in the middle column of Figure (2-5). The level factor in all countries increase, with the response of the level being faster and stronger in Norway and South Korea whilst for the US and Canada such responses were not statistically significant.

The slope factor in oil importing countries (the US and South Korea) increased after aggregate demand shocks, which is consistent with the central bank's policy reaction using conventional Taylor rules, as shocks to aggregate demand move output and price in the same direction requiring tightening monetary policy. The increases in slope is more prominent in South Korea, which may be related to its higher dependency on oil (and its products) in its role as input to production and as a consumption good. The impact of the shocks on the slope on the Canadian yield curve is negligible, indicating a very mild response of the central bank to the shock. A more surprising result is the response of the same factor in Norway, where the yield curve steepens, contrary to conventional expectations regarding the reaction of monetary policy, suggesting that the shocks have resulted in increases in the long-rate as investors assess the reaction of the short rate was not sufficient to control future expected inflation.

Oil Market-Specific Shock

The last column of Figure (2-5) shows the responses of the yield curve factors to oil market-specific demand shocks. The levels in the US, Canada, and South Korea increase for around six months; this response can be understood as the effect of the high real price of oil and related products on inflation. It is interesting to see

that level decreases significantly in Norway. This negative responses of the yield curve level in Norway might be due to the expected currency appreciation.

In the investigation to provide some potential explanations for a decline of the inflationary pressure from oil price rises in the 2000s, Chen (2009) argues that the appreciation of the domestic currency has been one of the major causes. Basher et al. (2016) study the responses of exchange rates to the different sources of oil shocks and show that currencies of oil-exporting countries appreciate after oil market-specific demand shocks, but find no significant patterns in the adjustment of exchange rates after oil supply and aggregate demand shocks in both oil-exporting and oil-importing countries. Buetzer et al. (2012) and Buetzer et al. (2015) find that oil exporters tend to counter appreciation pressures after an oil demand shocks by accumulating foreign exchange reserves and sovereign wealth funds. The authors argue that these counter-balancing forces, preventing large fluctuations in the nominal exchange rates, are the main reason for finding no clear relationship between oil prices and exchange rate movements as theories imply. However, the countries, especially with floating currencies, still experience a nominal appreciation following oil demand shocks.

The significant increases of slopes in all countries are consistent with Kilian (2009)'s argument that oil market-specific shocks, associated with precautionary demand for oil, have been the main driver of real oil price fluctuations and act as the largest inflation pressure.

Term structure curvature responses vary across countries. In the US, the initial response is decreased curvature indicating a relative fall in mid-maturity rates, stemming, in all probability from the response of the level, and the temporal marked rise in the short rate; subsequently these pressures on the short rate abate

and the curvature returns to its previous value. The responses are possibly related with the expectations over output deterioration due to the negative impact of the oil price hike. It can also be understood as a result of the systematic policy response offsetting the anticipated inflationary effect (see, for example, Bernanke et al. 1997) in the medium term. There is no immediate reaction in Canada, after a period of two-three months the curvature increases, indicating a possible over-reaction of the the mid-maturity rates to the tightening of monetary policy and steady level factor. Eventually as short rates return to their pre-shock level the curvature returns to its equilibrium value. In Norway the small decrease in the level factor associated with an increase in the short rate puts upwards pressure on the mid-maturity rates, increasing temporarily the curvature of the yield curve. As the short rate begins to fall and the long rate returns to its previous value, this pressure subsides and the yield loses concavity. Finally in the case of South Korea, initially all neighbouring rates (to the short rate) move together leaving the curvature unchanged for up to a year after the shocks. Subsequently as short rate falls, is followed by an accelerated decrease in the mid-maturity rates, manifesting as a falling curvature of the South Korean yield curve.

Yield Curves after the Shocks

To describe the entire term structure dynamics after each oil price shock, in Figure (2-6), we provide the changing shape of yield curve after selective months from the shocks. Each row represents the country-specific yield curve and each column shows the shocks to oil supply, aggregate demand, and oil market-specific demand. The curves with a solid line are average yield curve for estimation periods. The dotted and dash-dot line are for the yield curve after 3 and 12 months, respectively. The dashed line represents the yield curve after 24 months.

To the shocks in oil supply disruption, the US yield curve becomes steeper during the first six months which is related to monetary policy response. However, as expectations over the future negative impact on growth dominate, the yield curve begins to shift downwards after 12 months. In Canada, the dynamics of yield curve show a similar pattern to the US, but the magnitude is slightly larger than that of the US. The yield curves for Norway and South Korea react more to oil price shocks, both in terms of position and shape, which is reasonable as these two countries are more exposed to oil shocks. The yield curve for Norway shifts upwards after an oil supply shock and returns below its initial level after 24 months, whilst in South Korea following the initial shift upwards the yield curve is set at a lower level but above its original position.

Aggregate demand shocks have smaller impact on the dynamics of the term structure of interest rates in all four countries. For oil exporting countries such as Canada and Norway the yield curve settles eventually at below its pre-shock level, the difference is more pronounced in the case of Norway. For both the US and South Korea the total effect after 24 months is almost negligible.

In most cases, following an oil market-specific demand shock the yield curves shift upwards in the immediate aftermath, in line with Kilian (2009)'s finding that oil market-specific shocks have the largest impact on the real price of oil which implies its highest influence on inflation expectation despite the policy rate response to moderate its impact on overall price. Generally speaking the yield curves after 24 months have become steeper, lying below their original levels, with the short rate remaining at the same level in the US and Canada and falling in Norway and South Korea. This is due to the dominant negative effect on output following such shocks. In this case, central banks eventually reduce short rates pushing downwards all the near-by maturities.

2.5.3 Variance Decompositions

To quantify the importance of the structural shocks in global oil market on the dynamics of the yield curve, Table (2.2) reports the forecast error variance decompositions of the three yield factors to oil supply, global aggregate demand, and oil market-specific demand shocks.

Panel A of Table (2.2) shows the results for the US. On impact, the effect of three identified global oil market shocks on the level, slope, and curvature are negligible, with 1.0%, 1.2%, and 0.5% of total variability in the respective factors associated with all the shocks from the global oil market. The variability of level accounted by oil market shocks increases to 4.0% after 12 months with most of the effect coming from oil market-specific demand shock. Global oil market shocks do not explain much for the US slope factor, only 4.6% is explained by them after 60 months. Aggregate demand and oil market-specific demand shocks have non-negligible explanatory power on the yield curve curvature, accounting for more than 10% after 24 months.

The results of the decomposition of the forecast errors variance for the Canadian yield factors are summarised in Panel B of Table (2.2). After 12 months, shocks in global oil market shocks account for around 5% of the forecast error variance, of the level factor, similar share for the slope and up to 9.5% for the curvature. However, over time, and after 48 months these proportions rise to 9.3%, 6.3% and 19.9% respectively, evidence that impact of oil shocks, from different sources, have a pronounced medium term effect on both the slope, level and curvature of the yield curve.

Panels C and D of Table (2.2) show that innovations from global oil market

explain a large part of the forecast error variance of the yield factors in Norway and South Korea. Initially, the variances of the level factors are mainly explained by their own innovations. However, along longer forecast horizons, say 12 months or more, at least 20% of the forecast error variances of these factors are explained by the oil market shocks, and these proportions increases significantly after 48 months. The same pattern emerges in the case of the variance decomposition of the slope and curvature factors for both countries.

More specifically oil market-specific demand shocks explain a considerable proportion of the forecast error variable of the interest rates level in Norway. They account for around a third of the level variance among the overall variances due to oil price shocks after 12 months and the proportion rising to 61.9% after 48 months, whilst for the slope, the shocks account on the average for 80% of the slope variance over the same time span. Regarding the shocks impact on the decomposition of the variability of the curvature forecast error the share rises from 46.9% to 63.0%, indicating the increasing importance of this type shock on Norway's yield curve.

In the case of South Korea, more than 36% of the variability of each yield factor can be attributed to the presence of the shocks within the first 24 months and the share remains stable, albeit with different decomposition, over the 60 month period. Interestingly, oil supply shocks have large explanatory power for the variance of the forecast errors of level factor in South Korea after the first 12 months, thereafter its importance decreases somewhat after 36 months. The shocks' impact on the variance of the slope and curvature rises fast reaching almost 20% within the same period.

It is of interest that aggregate demand shocks have a modest but very steady impact on all the factors of the yield curve, indicating a very modest movement of

the yield curve. Oil market-specific demand shocks explain a substantial proportion of the variance of South Korean yield slope. It is remarkable that whilst within 12 months in contribution is only 2.8%, by the end of month 48 this has risen to 15.7%, whilst for slope and curvature this shock accounts for 17.8% and 15.7% respectively.

Although since late 2008 nominal short-term interest rates have assumed almost zero values and the long-term rates have been below 4% and interest rates in other economies have also recorded on unprecedented low level, this analysis has established the importance of the impact of shocks from the global oil markets on the shape and positions of the yield curves for four countries. Our result suggests that there is no universal outcome from such shocks and that their impact has to be calculated on a country basis taking into account its position as an oil exporter or importer. Whilst the yield curve of large economies as the US do not exhibit substantial changes after such innovations, for small open oil importing economies like Norway and South Korea, such incidents have pronounced and persistent impact on their financial markets as bond yields are affected by oil shocks.

2.5.4 Robustness Check

We next consider the impact of oil market shocks on the yield curve by considering the period from the beginning of the available sample to the end of 2008, where interest rates were fluctuating near their historical levels. From the onset of the financial crisis, financial and commodity markets witnessed a truly unusual conduct of monetary policy in almost all Western economies. Policy rates in the US have reached to all intents and purposes the zero lower bound and have been kept at

this rates for almost 9 consecutive years. For example during the first period the average three-month rate is 6.2% and the ten year rate 7.5%. From January 2009 the same maturity rates averaged 0.2% and 2.7% respectively. Over the same period in Canada, the impact of the financial crisis was less pronounced. Although the yield curve shifted downwards, the average of the the three month rate was around 1% compared to its before crisis mean of 5.7% and the long-term rates have also declined from 6.8% to 2.5%.

The previous analysis is based on the whole data sample that is constituted by these very distinct periods regarding the statistical behaviour of the yield curve, both in terms of position and shape. The limited number of data points available in the aftermath of the financial crisis does not allow for the separate econometric analysis from January 2009. To examine the possible future impact of the oil shocks in a period where interest rates are set without reference to the immediacy dictated by the financial crisis, we conduct the same econometric analysis over the pre-crisis period only. This exercise will allow to test whether the current unusual conduct of monetary policy has cushioned the impact of oil market shocks on the yield curves of the US and Canada.

Figure (2-7) reports impulse response of three yield factors to oil price innovations. The effect of an oil supply shock has no initial discernible effect on the level, slope and curvature factors. Over the subsequent periods there is a predicted decrease in the slope and a corresponding increase in curvature implying a fall in the short rate to ameliorate the predicted impact of the shock on output. The major impact on the US yield curve is due to oil market-specific demand shocks. In this case there is a strong and persistent increase of the level factor, followed by a corresponding increase in the slope and decrease in curvature. The response is qualitatively similar to the one calculated using the whole sample period, however

in this case unlike the previous, the impact of the shock on the level is significant and very persistent. This may signify that once interest rates return to their previous levels the sensitivity of the yield curve to oil market shocks will far more noticeable.

There is also a remarkable increase of the contribution of the same shocks on the variance decomposition of the level, slope and curvature factors as reported in Table (2.3). These now stand at 7.1%, 5.2% and 10.0% after 12 months, compared to 4.0%, 2.9%, and 9.2% when the whole sample was used, and the equivalent contributions after 48 months now stand at 17.2%, 5.2% and 11.3% rather than 2.6%, 3.7% and 10.9%. The main conclusion from this analysis is that this type of oil market disturbances cause substantial increases of the ‘equilibrium’ rate of interest during ‘normal’ periods. Currently the extremely low rates of interest provide for a protective cushion, keeping such rate unaffected.

In Canada, similarly to the US an oil supply shock does affect the level and has a strong and persistent affect on the slope. The slope declines, implying a fall of the short-term rate. This finding is consistent with the expected response of any central bank to the expected fall in activity, following such an oil marker disturbance. Unlike the case of the US, oil market-specific demand shocks exercise downward pressure on the level factor and tend to flatten the yield curve as short rates are rising whilst the long rate tends to fall, as the slope rises. It seems that the reaction of the Canadian central bank to this shock, by raising the short rate, is sufficient signal to indicate lower future inflation, pushing downwards the long rate. Aggregate demand shocks lead again the short-term rate rises, flattening the yield curve and this impact is more pronounced during the pre-crisis period. These findings point towards the existence of a ‘recent reluctance’ by the Central Banks to raise the short rate in the presence of oil market shocks. The contributions of

these shocks to the variance decomposition of the three factors is higher overall in both 12 month and 48 month horizons, with marked increased contributions in the level and curvature factors. The more striking point from this analysis is that in both countries we found that the level factor was far more sensitive to oil market shocks in the pre-crisis period.

2.6 Conclusion

We study the impact of the oil price shocks on the term structure of interest rates across four industrial countries; the US, Canada, Norway, and South Korea. Our results indicate that the yield curve factors (level, slope, and curvature) react differently to oil market shocks contingent on the underlying sources that drive them, the country's dependence on oil, and the manner of conduct of monetary policy.

Undertaking the analysis over the whole sample, we find that oil market-specific demand shocks result in increases of level factor in oil-importing countries, whilst have no such effect in oil-exporting countries. Oil supply disruptions have short-lived negative responses of the slope factors in the US and Canada, associated with the loosening of monetary policy, whilst demand side shocks lead to slope increases in all countries, resulting from short-term rate rises. The supply and demand shocks jointly account for a considerable amount of the observed variation in the term structure of interest rates, explaining up to almost half of the changes of the South Korea, 20% in Canada and Norway, whilst have limited impact on the US. It is evident that South Korea as net oil importer is relatively very sensitive to oil market fluctuations, compared to oil exporting countries like Canada and

Norway. The combined contribution of these shocks to the variance decomposition of the US yield curve is limited to approximately 10%.

Despite the significant variations between the four countries, found on the impact of oil market shocks, we established that all yield curves respond via some factor. This effect has been neglected in the literature as it has focused almost exclusively on macroeconomic aggregates and their relationship with financial variables has been limited in stock market. Our results suggest that oil shocks independently of their sources will affect the discount factors as they alter the position and shape of the yield curves.

Sub-sample estimation exercise reveals that the unusual monetary policy condition during the crisis time had altered the relationship between oil price and the term structure of sovereign yields. For both the US and Canada we find that the impact of these shocks on yield curve is more noticeable and persistent. The current monetary policy, keeping extremely low policy rates, has limited the impact of oil markets developments on the factors of the yield curve, providing additional stability in these rather uncertain times.

Table 2.1: Summary Statistics for the Full and Sub-Sample Periods

		3M	2Y	5Y	Level	Slope	Curvature
United States	1973M1 - 2015M12	5.20	5.67	6.19	6.72	-1.52	-0.59
	1973M1 - 2008M12	6.17	6.66	7.09	7.50	-1.33	-0.34
	2009M1 - 2015M12	0.24	0.54	1.55	2.74	-2.51	-1.90
Canada	1986M1 - 2015M12	4.56	4.89	5.35	5.81	-1.25	-0.60
	1986M1 - 2008M12	5.72	6.03	6.44	6.81	-1.09	-0.47
	2009M1 - 2015M12	0.77	1.14	1.77	2.53	-1.76	-1.02
Norway	1998M1 - 2015M12	3.56	3.56	3.78	4.15	-0.58	-0.59
	1998M1 - 2008M12	4.81	4.75	4.85	5.03	-0.23	-0.33
	2009M1 - 2015M12	1.61	1.69	2.11	2.75	-1.14	-0.98
South Korea	2001M1 - 2015M12	3.51	4.02	4.34	4.67	-1.16	-0.14
	2001M1 - 2008M12	4.42	4.94	5.18	5.49	-1.07	-0.03
	2009M1 - 2015M12	2.47	2.97	3.39	3.74	-1.27	-0.27

Notes: This table reports the average values of the yields with 3, 24, and 60 months maturities. The level, slope, and curvature in this table represent the average values of the empirical counterparts for the yield factor estimates, and are calculated as $y_t(120)$, $y_t(3) - y_t(120)$, and $2 \times y_t(24) - (y_t(3) + y_t(120))$, respectively.

Table 2.2: Yield Curve Factor Variance Decomposition

Periods	Oil supply shocks	Aggregate demand shocks	Oil demand shocks	Level	Slope	Curvature	Oil market shocks aggregated
<i>Panel B. Yield Factors Variance Decomposition for the US (Jan 1973 - Dec 2015)</i>							
<i>(Level)</i>							
1	0.000	0.005	1.043	98.951	0.000	0.000	1.049
12	0.157	1.318	2.478	89.342	2.144	4.561	3.952
24	0.108	0.759	1.623	78.012	14.326	5.173	2.489
36	0.102	0.875	1.417	59.435	30.401	7.769	2.394
48	0.115	1.200	1.330	46.822	40.700	9.833	2.645
60	0.126	1.407	1.243	40.235	46.072	10.917	2.777
<i>(Slope)</i>							
1	0.727	0.133	0.364	14.250	84.527	0.000	1.223
12	1.164	0.724	1.043	7.537	82.065	7.467	2.931
24	1.088	0.570	0.792	5.542	79.639	12.369	2.450
36	1.074	0.555	1.172	5.204	79.068	12.926	2.802
48	1.077	0.717	1.952	5.189	78.212	12.853	3.746
60	1.073	0.966	2.557	5.167	77.475	12.762	4.596
<i>(Curvature)</i>							
1	0.074	0.010	0.420	16.098	0.034	83.364	0.504
12	0.716	6.698	1.756	8.299	3.170	79.360	9.170
24	0.804	6.527	3.270	7.326	4.511	77.564	10.600
36	0.745	5.868	4.068	7.778	7.953	73.588	10.681
48	0.714	5.370	4.808	8.613	11.380	69.115	10.892
60	0.694	5.246	5.436	9.008	14.050	65.566	11.376
<i>Panel B. Yield Factors Variance Decomposition for Canada (Jan 1986 - Dec 2015)</i>							
<i>(Level)</i>							
1	0.000	0.217	0.928	98.855	0.000	0.000	1.145
12	0.809	1.989	1.646	86.416	1.127	8.013	4.444
24	0.744	1.474	1.910	77.552	5.790	12.530	4.129
36	1.157	2.536	2.241	59.500	17.834	16.732	5.934
48	1.468	5.251	2.541	48.024	24.494	18.222	9.260
60	1.682	9.270	2.917	41.938	25.948	18.245	13.869
<i>(Slope)</i>							
1	1.233	0.008	0.087	6.166	92.505	0.000	1.329
12	2.093	0.265	2.345	4.094	83.586	7.617	4.703
24	1.724	0.223	3.888	2.764	80.605	10.796	5.835
36	1.680	0.245	4.321	2.808	79.865	11.081	6.247
48	1.683	0.251	4.339	2.811	79.836	11.081	6.272
60	1.689	0.253	4.340	2.810	79.817	11.091	6.282
<i>(Curvature)</i>							
1	0.458	0.084	0.327	12.952	1.045	85.134	0.869
12	3.574	3.297	2.585	6.544	4.641	79.360	9.455
24	6.755	4.577	8.004	9.601	8.330	62.732	19.336
36	7.026	4.642	8.089	11.543	7.995	60.706	19.756
48	7.140	4.612	8.101	11.718	8.355	60.075	19.852
60	7.202	4.625	8.087	11.813	8.508	59.765	19.914

Notes: This table reports percent contributions of oil price shocks to each term structure factor. The forecast error variance decomposition is obtained using the structural VAR model described in the text. The last column is the sum of the contributions of the three oil price shocks in explaining the factor variances.

Table 2.2: Yield Curve Factor Variance Decomposition (continued)

Periods	Oil supply shocks	Aggregate demand shocks	Oil demand shocks	Level	Slope	Curvature	Oil market shocks aggregated
<i>Panel B. Yield Factors Variance Decomposition for Norway (Jan 1998 - Dec 2015)</i>							
<i>(Level)</i>							
1	0.032	1.953	0.072	97.944	0.000	0.000	2.056
12	7.376	11.505	8.520	67.873	3.240	1.486	27.401
24	5.267	8.434	7.711	54.050	4.602	19.936	21.412
36	3.526	5.873	11.243	46.033	2.993	30.333	20.641
48	4.313	5.983	16.746	43.162	2.464	27.332	27.043
60	5.260	6.895	19.251	40.898	2.452	25.244	31.407
<i>(Slope)</i>							
1	0.322	4.339	2.404	52.192	40.742	0.000	7.065
12	0.772	1.925	21.895	17.894	28.645	28.868	24.593
24	1.974	2.680	19.356	19.080	24.009	32.902	24.009
36	2.696	3.389	18.959	21.502	22.649	30.806	25.043
48	2.985	3.706	19.334	21.458	22.196	30.321	26.025
60	3.070	3.811	19.264	21.345	22.035	30.475	26.145
<i>(Curvature)</i>							
1	0.190	0.002	0.862	36.991	0.637	61.317	1.054
12	3.278	0.749	3.562	26.416	5.745	60.250	7.589
24	4.930	0.811	9.490	26.267	6.781	51.720	15.232
36	6.124	0.910	11.285	26.699	6.570	48.412	18.319
48	6.338	1.077	12.648	25.945	6.690	47.302	20.063
60	6.400	1.173	12.629	25.848	6.870	47.080	20.203
<i>Panel B. Yield Factors Variance Decomposition for South Korea (Jan 2001 - Dec 2015)</i>							
<i>(Level)</i>							
1	0.573	0.001	3.169	96.257	0.000	0.000	3.743
12	27.119	8.098	2.815	58.503	2.558	0.907	38.032
24	34.116	7.941	4.857	45.002	3.846	4.238	46.914
36	32.231	6.183	8.453	32.285	10.759	10.090	46.866
48	24.850	4.681	15.729	24.222	19.519	10.999	45.260
60	20.943	4.455	22.597	19.918	22.270	9.818	47.995
<i>(Slope)</i>							
1	0.146	0.782	0.070	68.495	30.507	0.000	0.997
12	0.668	7.927	23.286	25.958	40.153	2.009	31.881
24	7.466	9.343	19.627	20.559	40.526	2.479	36.436
36	13.605	9.806	20.555	17.366	35.481	3.187	43.966
48	19.256	9.141	17.824	14.988	34.785	4.006	46.220
60	18.723	8.522	19.544	13.952	34.722	4.537	46.789
<i>(Curvature)</i>							
1	1.574	0.520	0.001	0.158	0.224	97.523	2.095
12	15.572	8.233	10.897	4.352	4.671	56.275	34.702
24	15.130	9.611	14.291	6.418	4.825	49.726	39.032
36	19.884	9.269	13.587	6.065	7.148	44.047	42.740
48	18.784	8.391	15.722	5.916	10.684	40.504	42.896
60	17.908	8.134	18.789	5.571	11.995	37.603	44.831

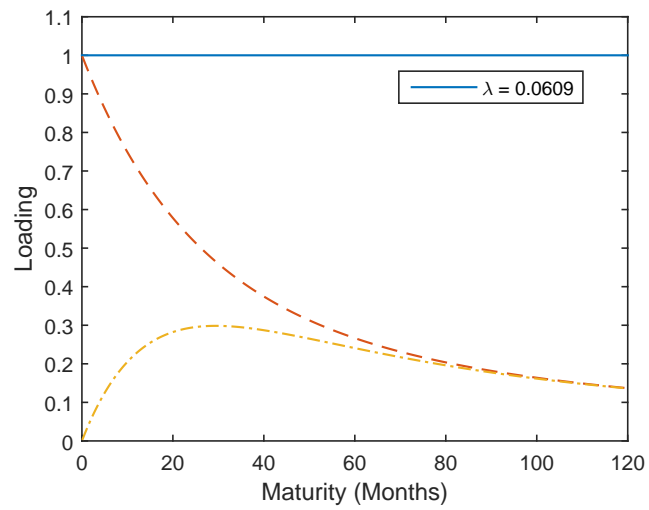
Notes: This table reports percent contributions of oil price shocks to each term structure factor. The forecast error variance decomposition is obtained using the structural VAR model described in the text. The last column is the sum of the contributions of the three oil price shocks in explaining the factor variances.

Table 2.3: Yield Curve Factor Variance Decompositon (Sub-Sample)

Periods	Oil supply shocks	Aggregate demand shocks	Oil demand shocks	Level	Slope	Curvature	Oil market shocks aggregated
<i>Panel B. Yield Factors Variance Decomposition for the US (Jan 1973 - Dec 2008)</i>							
<i>(Level)</i>							
1	0.006	0.859	0.945	98.190	0.000	0.000	1.810
12	0.118	0.562	6.404	80.891	3.430	8.594	7.084
24	0.172	1.267	9.476	66.378	17.743	4.965	10.915
36	0.224	2.437	12.792	48.472	31.921	4.154	15.453
48	0.200	2.604	14.413	36.904	40.371	5.508	17.218
60	0.172	2.315	14.734	30.468	44.799	7.513	17.220
<i>(Slope)</i>							
1	0.890	0.147	0.130	9.543	89.290	0.000	1.167
12	0.864	2.731	1.620	4.154	80.900	9.730	5.216
24	0.600	1.918	1.388	2.878	78.210	15.005	3.906
36	0.578	2.229	1.495	2.671	77.878	15.148	4.302
48	0.593	2.665	1.932	2.643	77.178	14.989	5.190
60	0.600	2.793	2.186	2.658	76.780	14.983	5.579
<i>(Curvature)</i>							
1	0.085	0.703	0.484	14.162	0.008	84.558	1.271
12	1.024	6.453	2.535	6.828	2.876	80.284	10.012
24	1.024	5.649	5.302	7.508	3.736	76.780	11.975
36	0.988	5.520	5.174	9.916	7.824	70.577	11.682
48	1.003	5.492	4.802	11.217	12.044	65.443	11.296
60	1.021	6.400	4.650	11.314	14.066	62.549	12.071
<i>Panel B. Yield Factors Variance Decomposition for Canada (Jan 1986 - Dec 2008)</i>							
<i>(Level)</i>							
1	0.050	1.932	0.096	97.922	0.000	0.000	2.078
12	1.424	3.135	0.680	84.000	2.761	7.999	5.240
24	0.998	2.889	1.597	73.000	13.724	7.792	5.484
36	0.852	9.467	1.712	53.370	23.395	11.204	12.032
48	0.798	12.202	1.681	43.089	24.341	17.889	14.681
60	0.769	12.554	2.375	37.250	24.336	22.716	15.697
<i>(Slope)</i>							
1	0.867	0.264	0.071	7.365	91.434	0.000	1.201
12	2.094	0.484	2.048	5.117	83.632	6.625	4.626
24	1.719	0.535	3.102	3.576	81.521	9.546	5.356
36	1.687	0.833	3.371	3.645	80.540	9.924	5.891
48	1.687	0.937	3.390	3.649	80.377	9.960	6.014
60	1.693	0.958	3.458	3.640	80.190	10.060	6.110
<i>(Curvature)</i>							
1	0.201	1.152	0.126	13.122	0.815	84.583	1.480
12	3.271	9.700	4.148	6.723	4.095	72.063	17.119
24	5.716	17.691	9.479	7.078	6.641	53.396	32.886
36	6.086	17.171	9.089	8.951	6.796	51.907	32.347
48	6.195	18.090	8.923	9.118	6.794	50.880	33.208
60	6.260	18.051	8.984	9.167	6.868	50.669	33.295

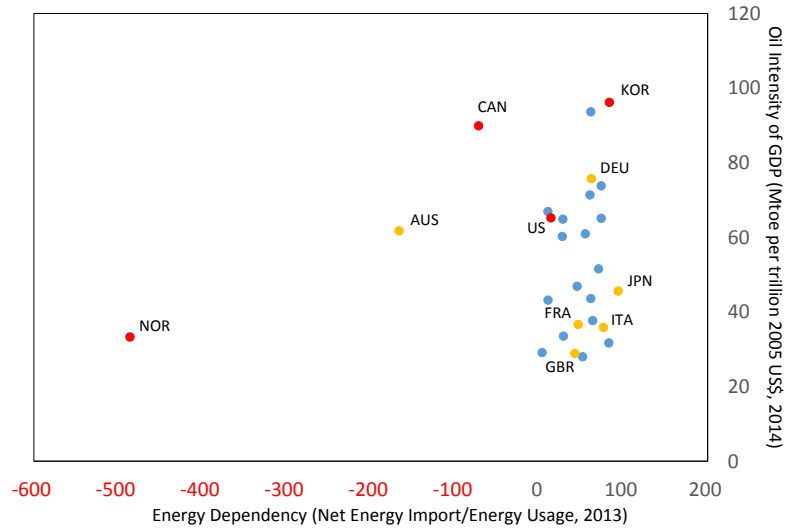
Notes: This table reports percent contributions of oil price shocks to each term structure factor. The forecast error variance decomposition is obtained using the structural VAR model described in the text. The last column is the sum of the contributions of the three oil price shocks in explaining the factor variances.

Figure 2-1: Loadings for Three Yield Factors

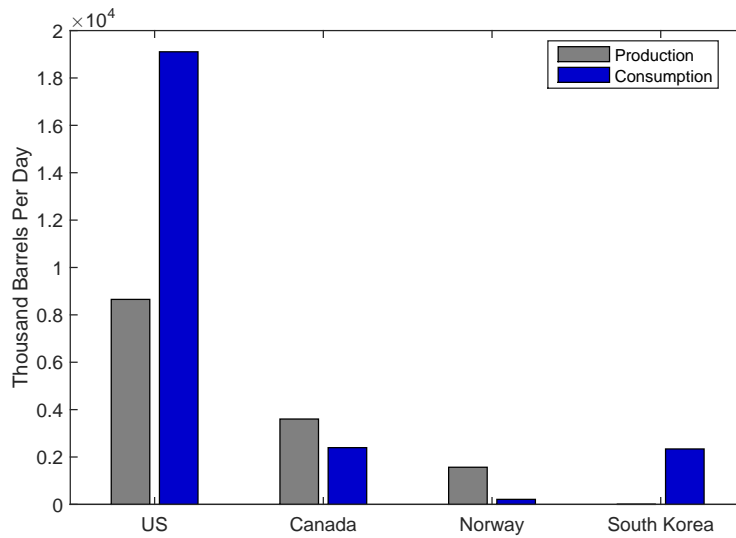


Notes: This figure shows the factor loadings as a function of maturities from 0 to 120 months, for $\lambda = 0.0609$. Solid line, which is constant at 1, represents the loading for level, decreasing dashed line is the loading for slope, and the dash-dot line is the loading for curvature. The value for λ is from Diebold and Li (2006).

Figure 2-2: Countries' Characteristics in Oil Production and Consumption



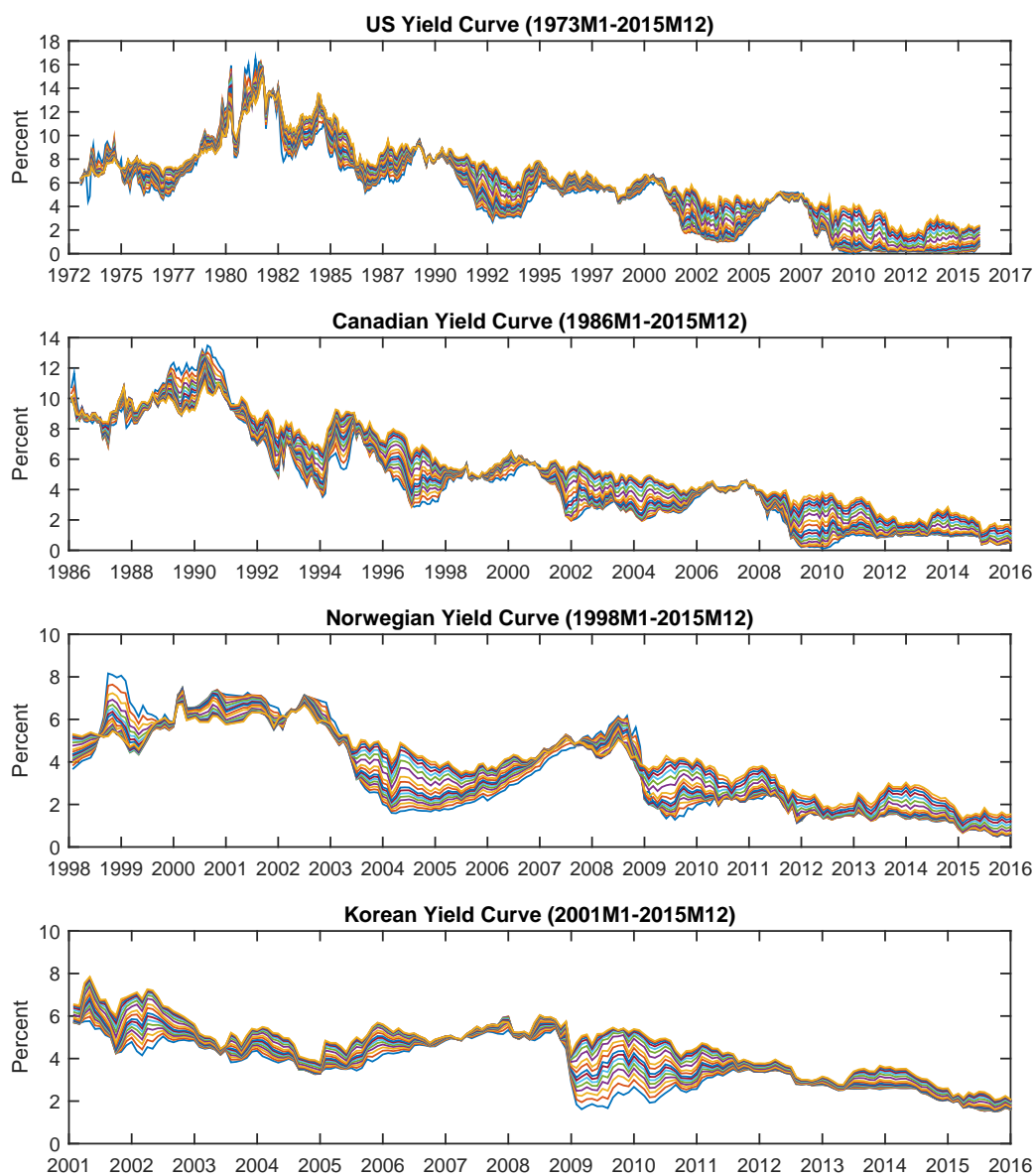
a. Energy Dependency and Oil Intensity of GDP



b. Crude Oil Production and Consumption

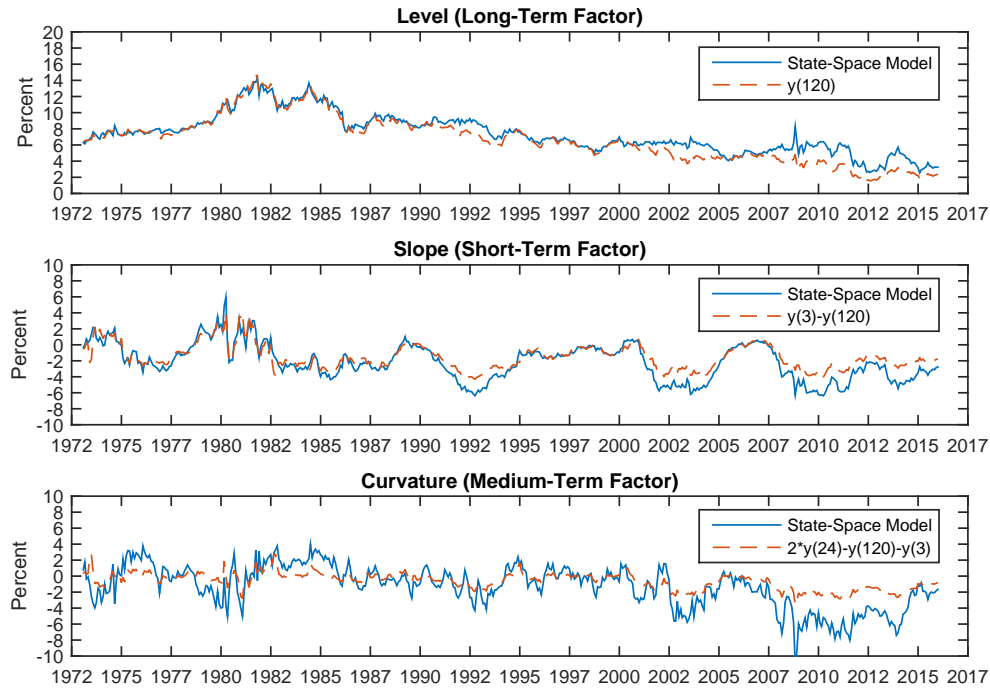
Notes: Energy dependency is net energy imports divided by energy usage as of 2013. Net energy imports are estimated by IEA (International Energy Agency) as energy use less production, both measured in oil equivalents. The oil intensity is the ratio of oil consumption (Mtoes) over gross domestic product measured in constant US dollar at market exchange rates as of 2014. Crude oil production and consumption are from IEA as of 2014. Crude oil production includes lease condensate.

Figure 2-3: Monthly Bond Yields

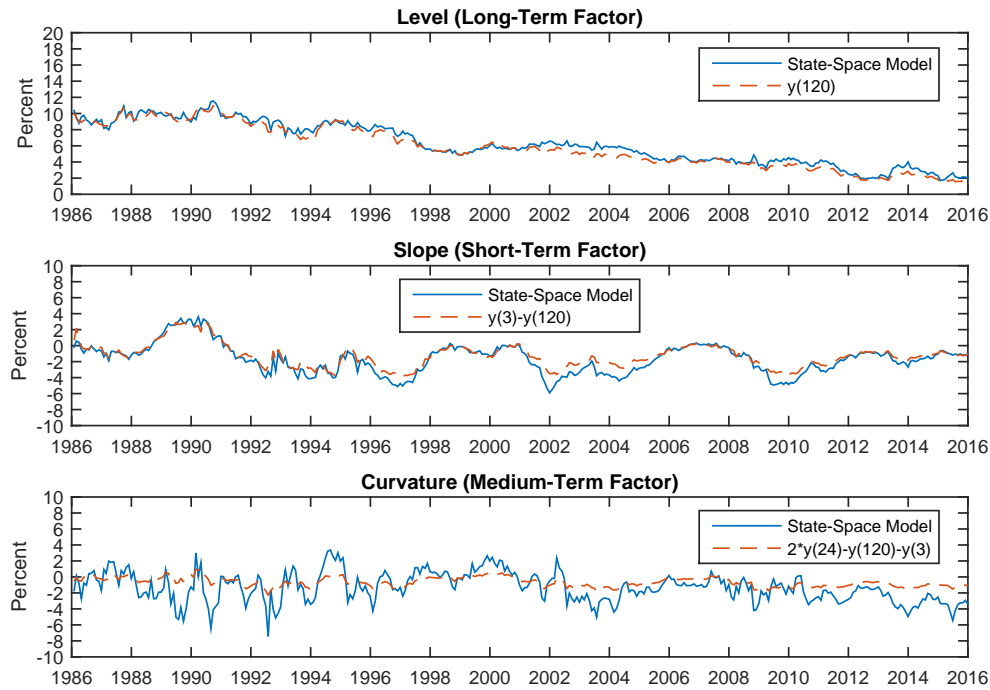


Notes: This figure shows end-of-month bond yields for the US, Canada, Norway, and South Korea. Each yield curve has 17 maturities (3, 6, 9, 12, 15, 18, 21, 24, 30, 35, 48, 60, 72, 84, 96, 108, and 120 months) used to estimate yield factors. The sample periods are different among countries due to availability.

Figure 2-4: Estimates of Level, Slope, and Curvature



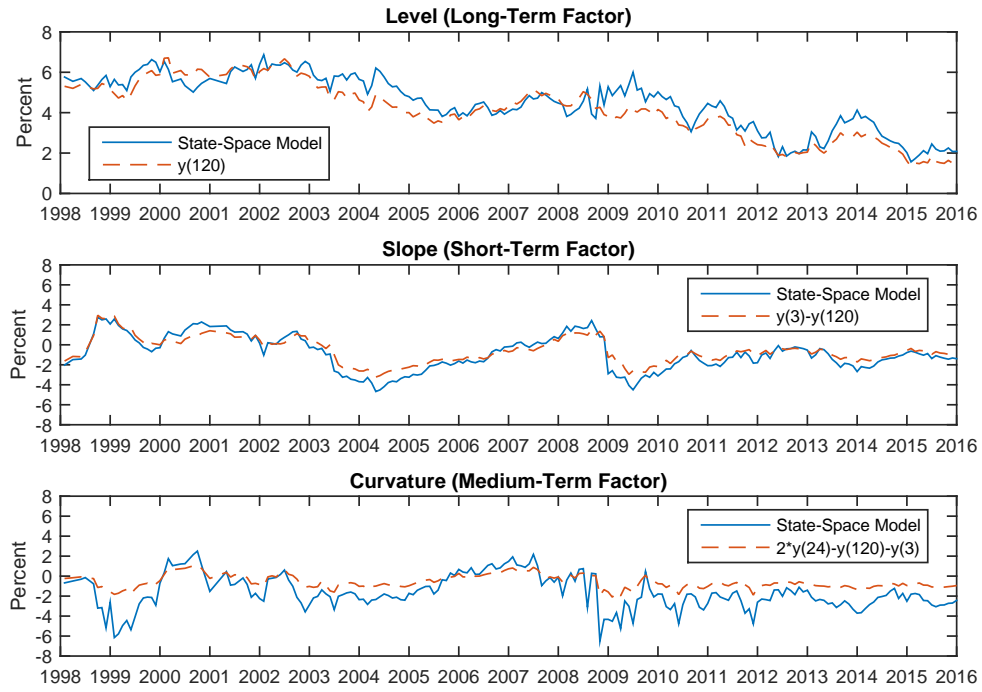
a. United States



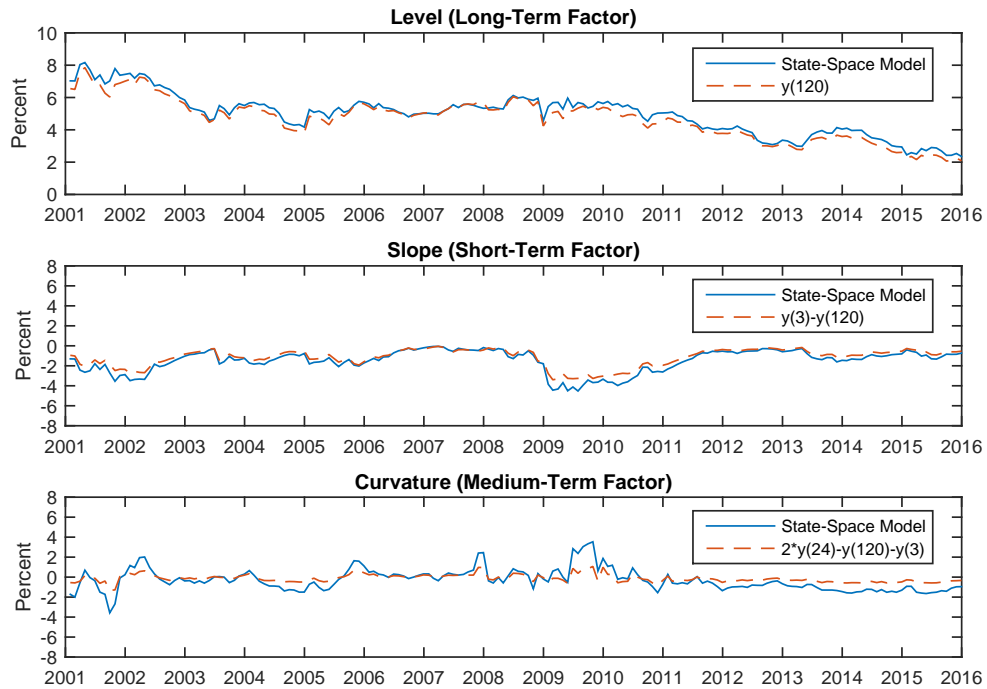
b. Canada

Notes: Solid lines are estimated yield factors (level, slope, and curvature for each country) using state-space model. We show empirical counterparts of the factors ($y_t(120)$, $y_t(3) - y_t(120)$, and $2 \times y_t(24) - (y_t(3) + y_t(120))$) with dashed lines.

Figure 2-4: Estimates of Level, Slope, and Curvature (continued)



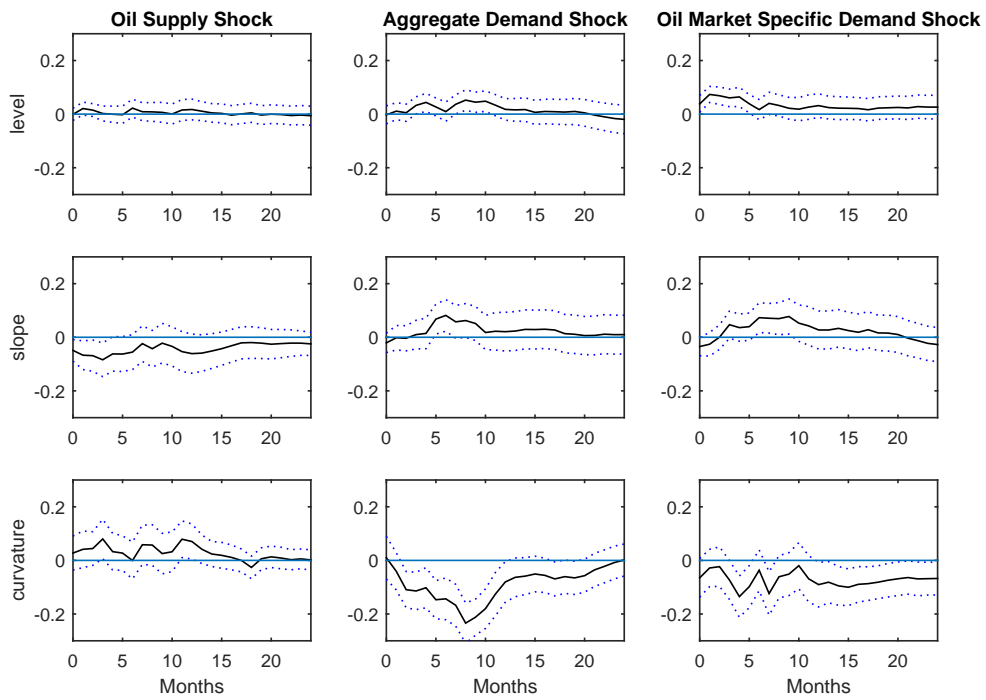
c. Norway



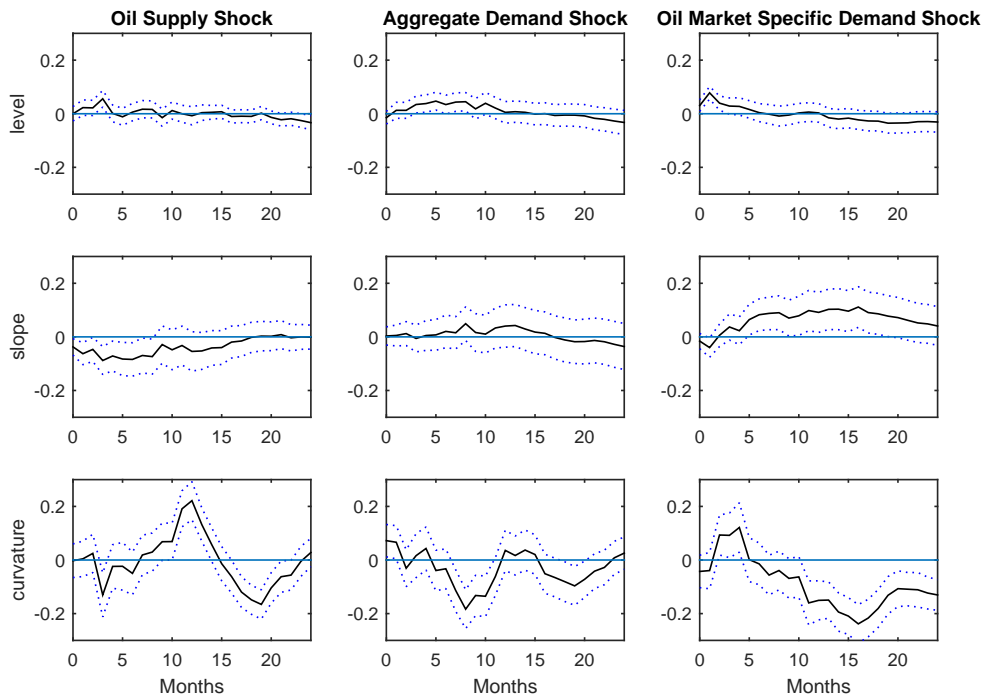
d. South Korea

Notes: Solid lines are estimated yield factors (level, slope, and curvature for each country) using state-space model. We show empirical counterparts of the factors ($y_t(120)$, $y_t(3) - y_t(120)$, and $2 \times y_t(24) - (y_t(3) + y_t(120))$) with dashed lines.

Figure 2-5: Responses in Yield Curve Factors to Structural Oil Market Shocks



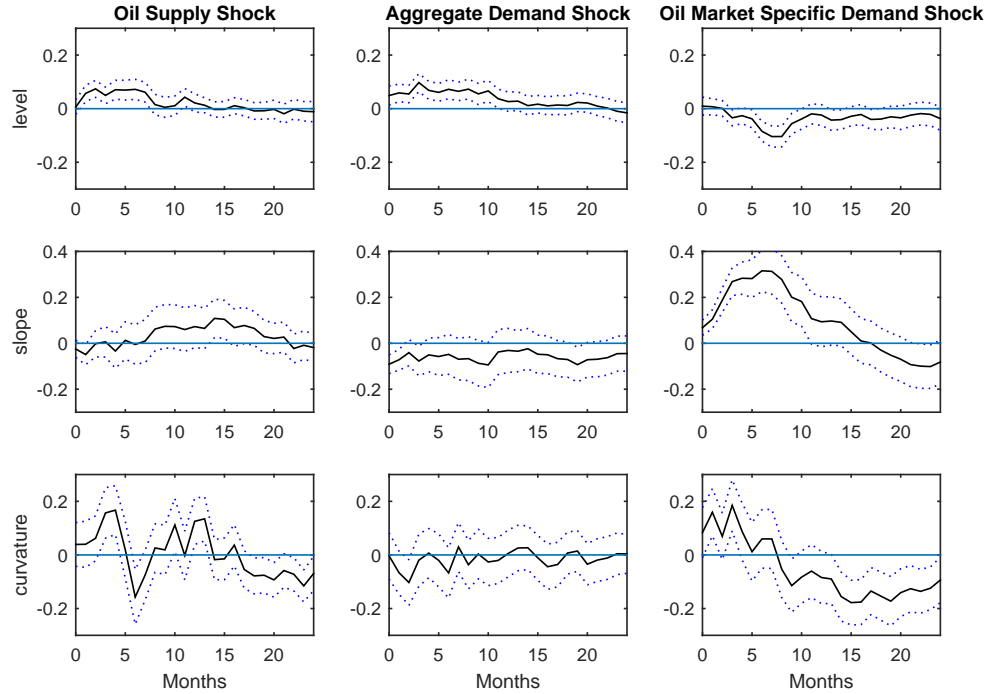
a. United States (Jan 1973 - Dec 2015)



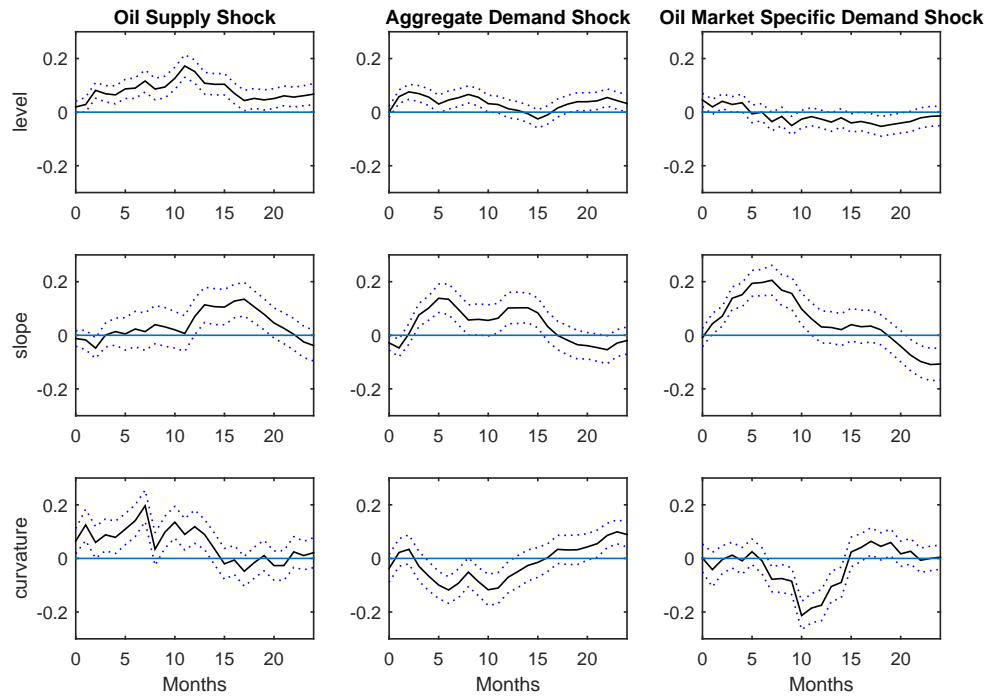
b. Canada (Jan 1986 - Dec 2015)

Notes: Responses are to one-standard deviation structural shocks in oil market shocks based on the SVAR model. Dotted lines represent one standard error bands constructed using a recursive-design wild bootstrap proposed by Gonçalves and Kilian (2004).

Figure 2-5: Responses in Yield Curve Factors to Structural Oil Market Shocks (continued)



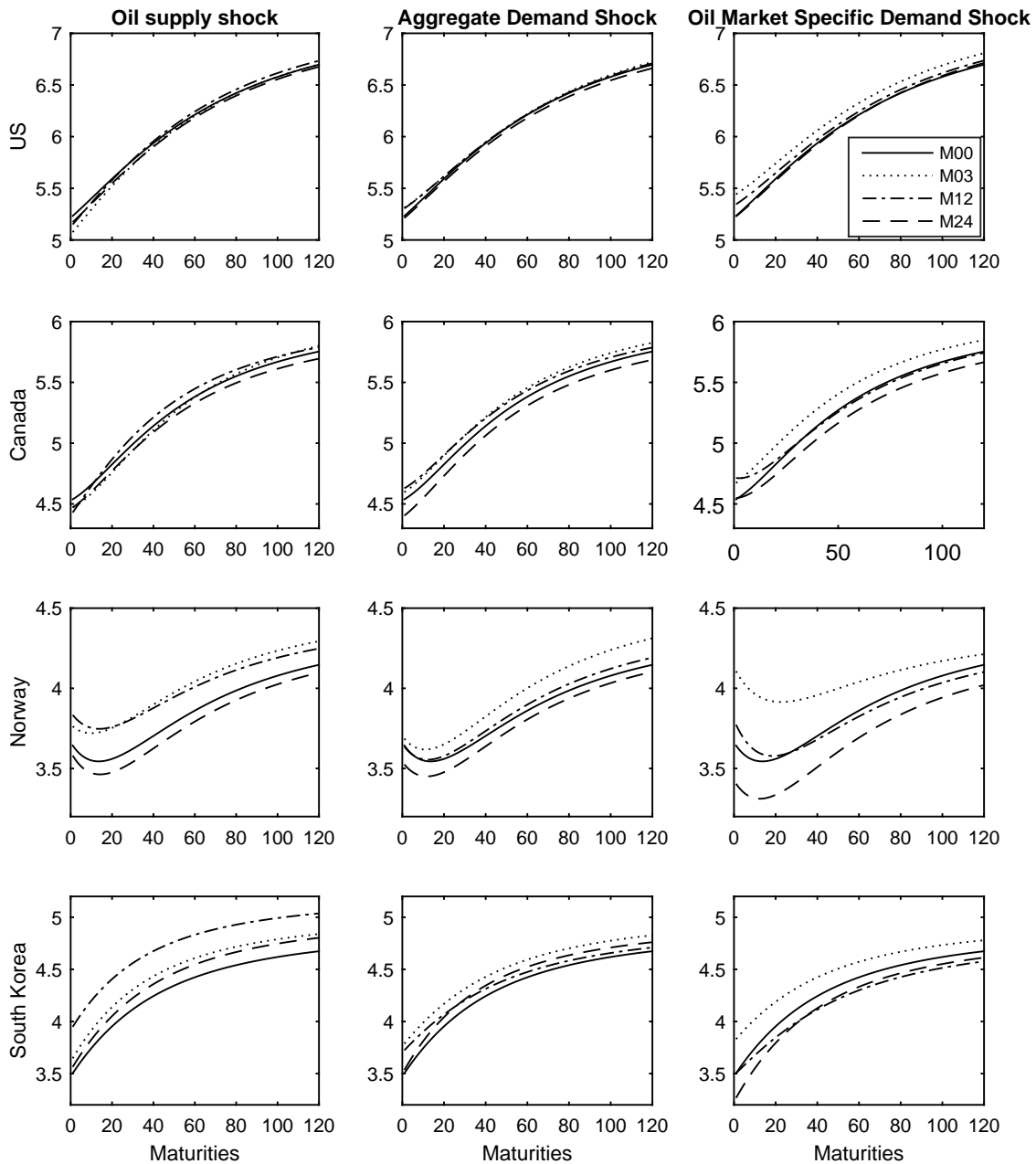
c. Norway (Jan 1998 - Dec 2015)



d. South Korea (Jan 2001 - Dec 2015)

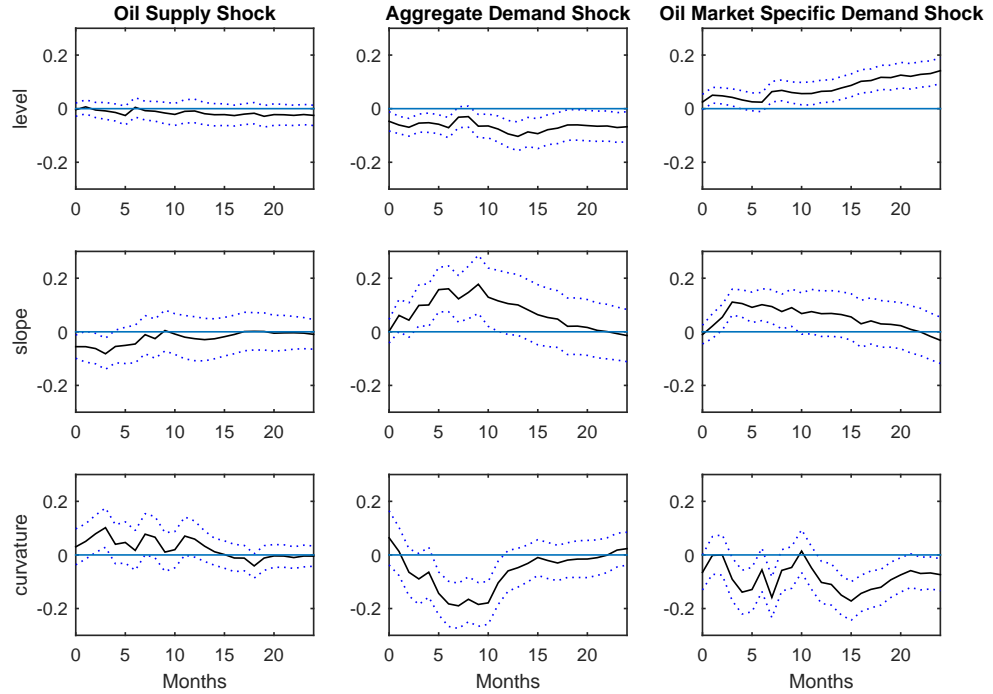
Notes: Responses are to one-standard deviation structural shocks in oil market shocks based on the SVAR model. Dotted lines represent one standard error bands constructed using a recursive-design wild bootstrap proposed by Gonçalves and Kilian (2004).

Figure 2-6: Yield Curve Dynamics after Oil Market Shocks (Full Sample)

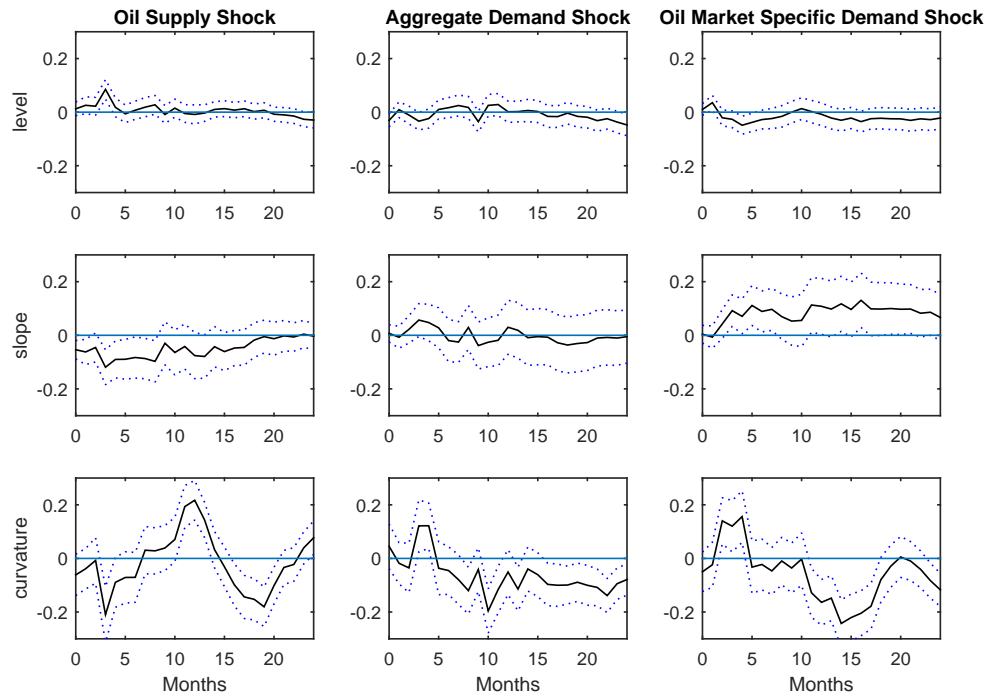


Notes: Figures show the changing shapes of yield curves in 3, 6, 12, and 24 months to three oil market shocks. Initial curves with solid line have the average shapes of the yield curves for the corresponding estimation periods.

Figure 2-7: Responses in Yield Curve Factors to Structural Oil Market Shocks (Sub-Sample)



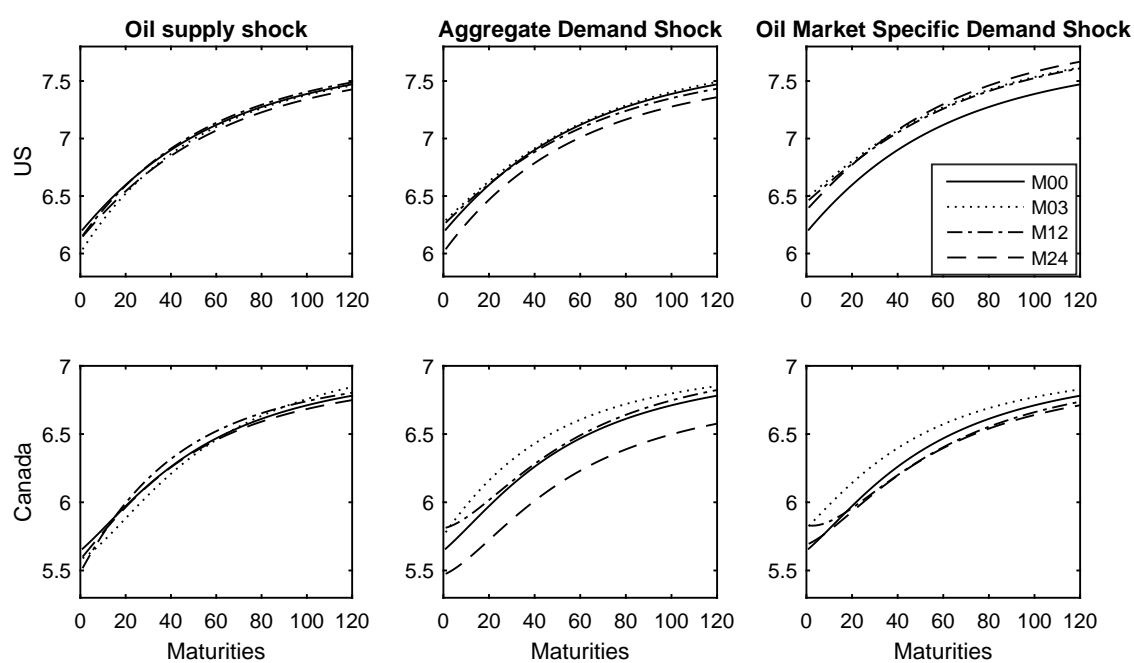
a. United States (Jan 1973 - Dec 2008)



b. Canada (Jan 1986 - Dec 2008)

Notes: Responses are to one-standard deviation structural shocks in oil market shocks based on the SVAR model. Dotted lines represent one standard error bands constructed using a recursive-design wild bootstrap proposed by Gonçalves and Kilian (2004).

Figure 2-8: Yield Curve Dynamics after Oil Market Shocks (Sub-Sample)



Notes: Figures show the changing shapes of yield curves in 3, 6, 12, and 24 months to three oil market shocks. Initial curves with solid line have the average shapes of the yield curves for the corresponding estimation periods.

Matlab codes for Chapter 2

(1) Impulse-response functions (for the US)

```

clc;
clear;
close all;

h=24;
maturities = [1:1:120];

%% US
sixvarUS

Ehat=inv(chol(SIGMA'))*Uhat(1:q,:);
q1tUS=Ehat(1,:); q1tUS=[(q1tUS(1,1)+q1tUS(1,2))/2 q1tUS];
q2tUS=Ehat(2,:); q2tUS=[(q2tUS(1,1)+q2tUS(1,2))/2 q2tUS];
q3tUS=Ehat(3,:); q3tUS=[(q3tUS(1,1)+q3tUS(1,2))/2 q3tUS];
q4tUS=Ehat(4,:); q4tUS=[(q4tUS(1,1)+q4tUS(1,2))/2 q4tUS];
q5tUS=Ehat(5,:); q5tUS=[(q5tUS(1,1)+q5tUS(1,2))/2 q5tUS];
q6tUS=Ehat(6,:); q6tUS=[(q6tUS(1,1)+q6tUS(1,2))/2 q6tUS];

[IRFUS]=irfvar(A,SIGMA(1:q,1:q),pUS,h);
    IRFUS(1,:)=cumsum(IRFUS(1,:));
    IRFUS(7,:)=cumsum(IRFUS(7,:));
    IRFUS(13,:)=cumsum(IRFUS(13,:));
    IRFUS(19,:)=cumsum(IRFUS(19,:));
    IRFUS(25,:)=cumsum(IRFUS(25,:));
    IRFUS(31,:)=cumsum(IRFUS(31,:));

% VAR bootstrap
rng('default')
NORep=2000;
IRFUSmat=zeros(NORep,(q^2)*(h+1));

[t,q]=size(z);
z=z';
Z=z(:,pUS:t);
for i=1:pUS-1
    Z=[Z; z(:,pUS-i:t-i)];
end;

Ur=zeros(q*pUS,t-pUS);
Yr=zeros(q*pUS,t-pUS+1);
U=Uhat;
for r=1:NORep
    pos=fix(rand(1,1)*(t-pUS+1))+1;
    Yr(:,1)=Z(:,pos);

```



```

eta=randn(1,size(Uhat,2)); eta=[eta; eta; eta; eta; eta; eta];
Ur(1:q,2:t-pUS+1)=U(1:q,:).*eta;

for i=2:t-pUS+1
    Yr(:,i)= V + A*Yr(:,i-1)+Ur(:,i);
end;

yr=[Yr(1:q,:)];
for i=2:pUS
    yr=[Yr((i-1)*q+1:i*q,1) yr];
end;
yr=yr';
[Ar,SIGMAr]=olsvarc(yr,pUS);

IRFUSr=irfvar(Ar,SIGMAr(1:q,1:q),pUS,h);
IRFUSr(1,:)=cumsum(IRFUSr(1,:));
IRFUSr(7,:)=cumsum(IRFUSr(7,:));
IRFUSr(13,:)=cumsum(IRFUSr(13,:));
IRFUSr(19,:)=cumsum(IRFUSr(19,:));
IRFUSr(25,:)=cumsum(IRFUSr(25,:));
IRFUSr(31,:)=cumsum(IRFUSr(31,:));
IRFUSmat(r,:)=vec(IRFUSr)';
end;

(2) Variance Decomposition (for the US)

%% US
sixvarUS

varstr.lags = pUS;
varstr.Sigma = SIGMA;
for i=1:pUS
    varstr.(['Phi_',num2str(i)])=A(1:q,(1+q*(i-1)):(q*i));
end
nperiods = 120;

vardecUS = var_decp_fn(varstr, nperiods)

for i=1:q
    for j=1:q

vardecreultUS.(['variable_',num2str(i)])(:,j)=vardecUS.(['shock',num2str(j)]
)(:,i);
    end
end

(3) VAR estimations (for the US)

```

```

load data_2015.txt;
z=data_2015;

load ('estimatedStatesUS_19732015.mat');
levelUS = estimatedStatesUS(:,1);
slopeUS = estimatedStatesUS(:,2);
curvaUS = estimatedStatesUS(:,3);

z=[z levelUS slopeUS curvaUS];
[t,q]=size(z);

pUS=12;
time=(1973+pUS/12+byUS/12:1/12:2015-eyUS/12+12/12)';

[A,SIGMA,Uhat,V,X,Y]=olsvarc(z,pUS);
SIGMA=SIGMA(1:q,1:q);

```

(4) Function: olsvarc

```

function [A,SIGMA,U,V,X,Y]=olsvarc(y,p);

global q

[t,q]=size(y);
y=y';
Y=y(:,p:t);
for i=1:p-1
    Y=[Y; y(:,p-i:t-i)];
end;

X=[ones(1,t-p); Y(:,1:t-p)];
Y=Y(:,2:t-p+1);

A=(Y*X')/(X*X');
U=Y-A*X;
SIGMA=U*U'/(t-p-p*q-1);
V=A(:,1);
A=A(:,2:q*p+1);

```

(5) Function: irfvar

```

function [IRF]=irfvar(A,SIGMA,p,h)

q=6;

```

```

J=[eye(q,q) zeros(q,q*(p-1))];
IRF=reshape(J*A^0*J'*chol(SIGMA)',q^2,1);

for i=1:h
    IRF=[IRF reshape(J*A^i*J'*chol(SIGMA)',q^2,1)];
end;

```

Chapter 3

Economic Policy Uncertainty and Bond Risk Premia

3.1 Introduction

Fundamental drivers of excess returns on financial assets have recently become a question of interest in macro-financial studies. Since Fama and Bliss (1987) and Campbell and Shiller (1991) addressed the empirical failure of the expectation hypothesis, literature has made much progress suggesting that the market price of risk varies over time and information in the current bond yields, for example, the slope of the term structure, have predictive ability for future bond returns. In line with these findings, Cochrane and Piazzesi (2005) have proposed that a single linear combination of the forward spreads contains remarkable information predicting excess returns on Treasury bonds. This strand of studies in financial economics, however, did not pay much attention to revealing macroeconomic fundamentals driving the factors' forecasting ability, that could provide invaluable knowledge for

policymakers and financial market participants.

Filling this gap, recent studies have attempted to find macroeconomic forces that predict future returns and the information content beyond the one contained in the current prices of financial assets. For example, Cooper and Priestley (2009) related excess holding period returns with variations in real economic conditions. Specifically, they have shown that the output gap, a variable representing business cycle fluctuations, serves as a strong predictor of stock and bond excess returns, conducting both in-sample and out-of-sample forecasting exercises.¹ Literature has followed connecting excess returns with a broader set of macroeconomic variables. Ludvigson and Ng (2009)’s work tests the predictive power of several factors summarising information in a large set of macroeconomic and financial variables.² Among the first eight principal components of the dataset, the factors closely related to “real activity” and “inflation” were shown to have strong predictive power for excess bond returns in US Treasury. They also found that affine term structure model incorporating the macro factors produces a distinct countercyclical yield risk premium, which is consistent with the findings in the previous studies such as Campbell and Cochrane (1999) and Wachter (2006).

Economic uncertainty has recently gained much attention as one of the factors containing return predictability in several theoretical and empirical studies

¹The using of synthetic variables such as the output gap is problematic as they are unobservable and need to be estimated. Orphanides and Van Norden (2002) have shown that the estimate of the output gap in real time is not reliable particularly due to the unreliability of end-of-sample estimates of the output trend. The finding implies that policy recommendations based on real time measure of output gap can be substantially differ from those obtained with ex-post revised data (Orphanides 2001). The usefulness of macroeconomic data for predicting excess bond returns are also found to be largely dependent upon the selection of data vintage (Ghysels et al. 2014), overstating the predictive ability of the information in macroeconomic data available in real time.

²Related studies include Joslin et al. (2014), Cieslak and Povala (2015), and Coroneo et al. (2016).

(see, Bollerslev et al. 2009; Wright 2011; Wright and Zhou 2009; D’Amico and Orphanides 2014; Kaminska and Roberts-Sklar 2015; Huang et al. 2015; Brogaard and Detzel 2015; Malkhozov et al. 2016; Grishchenko et al. 2017). Wright (2011), for example, has shown that uncertainty, measured by the dispersion of professionals’ inflation forecasts, serves as an important driver of risk premia in nominal yields. The variance risk premium, as a measure of volatility in asset prices, has also been shown to be a strong predictor of returns both in stock (Bollerslev et al. 2009) and in fixed income markets (Grishchenko et al. 2017). Providing theoretical underpinning, Pástor and Veronesi (2013) have established a general equilibrium model, in which the government’s protective role over the market is affected by economic uncertainty, thus uncertain policy demands additional premia, especially when the economic conditions are weak. In their model, policy heterogeneity in poor economic condition makes the uncertainty over policy choice more important generating higher volatility and risk premia in stock returns.

In this paper, we explore the empirical evidence linking economic uncertainty in government policies and bond returns. We use a measure of Economic Policy Uncertainty (*EPU*), which is developed recently by Baker et al. (2016). The index measuring the level of uncertainty in economic policy has been shown to be related closely to various macroeconomic and financial variables. For example, Baker et al. (2016) show that the *EPU* is associated with price volatility in the stock market and can forecast macroeconomic aggregates such as investment, output, and employment. Aastveit et al. (2013) find that the influence of monetary policy shocks becomes weaker when *EPU* is high. Karnizova and Li (2014) and Benati (2013) assess the ability of the *EPU* index to predict future recessions. The macroeconomic effects of *EPU* through the bank lending channel have been studied by Bordo et al. (2016), confirming that policy uncertainty has a significant

adverse impact on bank credit growth.

The advantages of using *EPU* as a potential predictor of bond returns are threefold. First, the uncertainty index can be computed as a near real-time measure, so it is free from publication delay and data revision. This advantage is not vulnerable to the issue of using macroeconomic data (or macroeconomic factors built on them) in return forecasting exercises. Indeed, Ghysels et al. (2014) document that data revisions in macroeconomic variables account for considerable amount of their in-sample and out-of-sample predictive power for bond returns.³ The issue is also relevant in the studies using information from the professional surveys. For example, in a study measuring macroeconomic uncertainty using the forecast errors of consensus survey, Jo and Sekkel (2017) found substantially different size of jumps in estimated uncertainty dependent on the selection of data vintage.⁴

Second, as the index is constructed based on the count of policy-related news,⁵ it is continuously collectable at different frequencies which enable us to test the high-frequency relationship between economic uncertainty and asset returns. By and large, empirical studies todate evaluating the impact of policy on asset pricing models have mostly employed event studies around infrequent policy changes such as elections (see, for example, Bernhard and Leblang 2006; Biłkowski et al. 2008; Boutchkova et al. 2012).

³They have found evidence that predictability using real-time macroeconomic data is considerably weaker. Adding information in survey forecasts, which is orthogonal to the real-time macro variables, is shown to help predict bond returns.

⁴Much literature has addressed that the evaluation of forecasting power of econometric models is largely dependant on the inclusion of different data vintage (see, for example, Diebold and Rudebusch 1991; Faust et al. 2003).

⁵*EPU* is constructed based on the frequency of articles in 10 leading U.S newspapers. To be counted as an uncertainty event, each article should contain three combinations of words related to “Economy”, “Uncertainty” and “Policy”. We provide details of construction in data section.

Third, we believe that the approach of measuring uncertainty based on news counts, unlike several alternative measures using asset prices in specific markets (for example, stock market volatility) or survey of small number of professionals (such as dispersion or economic forecasts), enables us to assess the level of uncertainty to which a wider range of economic agencies is exposed. In fact, evaluating economic uncertainty based on a broader information set, such as news publications and internet searches, is growing in popularity in financial studies.⁶

To examine the effect of fluctuating economic policy uncertainty on risk premia, our exercise tests the forecasting ability of *EPU* on bond excess returns of different maturities across various holding periods other than examining only a single holding period such as a year. This approach is in line with the recent studies finding return forecasting factors in short investment horizons. For instance, Mueller et al. (2012) show that market variance risk premium, as a proxy of economic uncertainty, has strong predictive power for the one-month horizon, but the relations disappear when testing with longer investment horizons. Gargano et al. (2017) suggest that studying the return forecasting-ability only for longer holding periods may inhibit efforts to identify short-lived dynamics in bond returns.

The growing attention in the high-frequency fluctuations of the risk premia is in line with studies such as Liu et al. (2016) and Crump et al. (2017).⁷ Common predictive regressions in the literature (for example, Cochrane and Piazzesi 2005; Ludvigson and Ng 2009, among many others) have estimated linear models with annual excess bond returns as dependent variables in regression equations using overlapping monthly observations. Bauer and Hamilton (2017) address the point

⁶See, for example, Rogers et al. 2016; Caporale et al. 2016; Da et al. 2011, 2015.

⁷Literature testing forecasting ability in monthly returns also includes Fricke and Menkhoff 2015, Lee 2016, and Grishchenko et al. 2017.

that estimation using bond returns, which are longer than the sampling interval, reduces the reliability of the regression results. To examine the possible issues in previous studies, they re-estimate the models published in six previous studies using their newly proposed test. Their exercise has shown considerable weakening of the empirical results, suggesting the literature does not support robust evidence against the spanning hypothesis.

Recent studies in the macro-finance literature explicitly incorporate macroeconomic variables or factors representing economic activities and inflation measures (Ang and Piazzesi 2003; Diebold et al. 2006, among many others), linking the dynamics of the term structure of interest rates to the fundamental macroeconomic determinants. The approaches in most macro-finance models, however, are based on the assumption that macroeconomic factors are entirely spanned by the current yield curve. This spanning hypothesis is contradicted by a large number of empirical studies testing for the predictive ability of macro variables for future excess returns (see, for example, Cochrane and Piazzesi 2005; Ludvigson and Ng 2009; Cieslak and Povala 2015).

In line with this criticism, Duffee (2011) uncovers the presence of a hidden factor which is not related to the cross sectional representation of the yield curve. Specifically, this factor is hidden from the information captured by the current yield curve, since its influence on the expectations of the future short-rate is cancelled out by the changes in term premia. The existence of hidden factor implies that a conventional model accommodating only the factors describing the cross section of yields could be misspecified. Joslin et al. (2014) also stress the existence hidden factors estimating a term structure model. Unlike the approach of Duffee (2011) who apply filtering to discover hidden factors, the authors include macroeconomic variables, representing output growth and expected inflation and

find that they are not entirely spanned by contemporaneous yields. Chernov and Mueller (2012) specify a term structure model that accommodates survey-based inflation expectations in addition to two macro variables (inflation and output) in both real and nominal yields. The authors argue that introducing survey-based forecasts of inflation helps to uncover the existence of hidden factor that has no effect on the nominal yields but clearly influence inflation expectations.

Motivated by the findings in return forecasting exercises, we incorporate *EPU* in a canonical affine term structure model as a candidate for hidden factors (Duffee 2011 and Joslin et al. 2011), unspanned by the current yield curve. Specifically, we estimate an affine term structure model with Cochrane and Piazzesi (2005)’s return forecasting factor and *EPU* in addition to the first three principal components representing the level, slope, and curvature of the yield curve.

Our empirical findings can be summarised as follows. Testing the impact of *EPU* on monthly US Treasury returns, we find that a one standard deviation increase in the *EPU* predicts a positive future excess return from 0.48% (1-year maturity, annualised) to 1.97% (5-year maturity) in 1-month holding period.⁸ We find that inclusion of *EPU* in addition to the factors extracted from current yield curve increases adjusted R^2 , implying *EPU* contains information predicting future returns, that is not spanned by the information in contemporaneous term structure. The size and significance of such effects have shown to be larger in near investment horizons in bonds with lower maturities, showing no statistically significant influence on 12-month investment horizon with all maturities considered. We interpret the result that *EPU* is more closely related to bond price volatility

⁸The finding is in line with Brogaard and Detzel (2015)’s empirical work based on the US stock index that the increase in *EPU* predicts positive expected excess returns. The size of effects on stock returns is larger than our results using Treasury bond returns, but the predictability for stock returns is more concentrated on 2 to 3-month investment horizons.

in higher frequency, implying that the influence of economic policy uncertainty almost disappears in investment horizons longer than six months.

To ensure that the strong predictability of *EPU* is an independent factors from those used in the literature, we add well-known return forecasting factors in the same exercises. Estimation results confirm that including the return forecasting factors from Cochrane and Piazzesi (2005) and Cieslak and Povala (2015) does not affect the predictive power of *EPU*. Controlling for other measures of macroeconomic and financial uncertainty from Jurado et al. (2015) and Ludvigson et al. (2017) does not change the results, suggesting that *EPU* captures variations in economic uncertainty which are related but distinct from alternative uncertainty measures. Our estimated expected returns using Adrian et al. (2013)'s three-step linear regression method explain a considerable amount of the fluctuations in observed returns. *EPU* has negligible influence on the current yield curves, but significantly forecasts positive excess returns, implying investors demand additional reward holding Treasury bond when the uncertainty in economic policy is rising. Comparing the estimated term premia with those from a model using only the factors summarising the information in contemporaneous yield curve, we find that adding the two factors generates more volatile and countercyclical term premia estimates, explaining a larger share of the variations in observed yield dynamics.

The rest of the paper is organised as follows: Section (3.2) discusses the affine term structure models methodology and the estimation procedure. Section (3.3) presents the description of the data and the sources. Section (3.4) provides the initial empirical findings regarding the relevance of *EPU* and other return forecasting factors for the predictability of bond returns at different maturities and different holding periods. Section (3.5) presents and discusses the results based on the methodology in Section (3.2). Finally, Section (3.6) concludes.

3.2 Term Structure Estimation

Canonical affine term structure models in finance treat yields as functions of a small number of latent(unobserved) factors such as level, slope, and curvature of the yield curve(for example, Dai and Singleton 2000; Duffee 2002). As the short rate and the price of risk are assumed to follow affine functions of state variables, then by imposing a no-arbitrage condition between yields on assets of various maturities, yields become affine functions of the state variables themselves.

3.2.1 Affine No-Arbitrage Model

The standard no-arbitrage affine term structure model (ATSM) assumes K risk pricing factors X_t following a first order VAR such as

$$X_{t+1} = \mu + \Phi X_t + v_{t+1}, \quad (3.1)$$

where the shocks conditionally follow the Gaussian distribution with variance-covariance matrix Σ , i.e. $v_{t+1} \sim N(0, \Sigma)$. The assumption of no-arbitrage implies that there exists a pricing kernel M_t that satisfies the pricing condition such as

$$P_t^{(n)} = E_t[M_{t+1}P_{t+1}^{(n-1)}], \quad (3.2)$$

where $P_t^{(n)}$ is the price of a bond with n -maturity at time t . The pricing kernel is assumed to be exponentially affine (Duffee 2002) as

$$M_{t+1} = \exp(-r_t - \frac{1}{2}\lambda_t'\lambda_t - \lambda_t'\Sigma^{-\frac{1}{2}}v_{t+1}). \quad (3.3)$$

The short-term interest rate $r_t = -\ln(P_t^{(1)})$ and the market prices of risk are assumed to be affine functions of the pricing factors:

$$r_t = \delta_0 + \delta_1' X_t, \quad (3.4)$$

$$\lambda_t = \Sigma^{-\frac{1}{2}} \lambda_0 + \lambda_1 X_t. \quad (3.5)$$

where δ_0 is a scalar and δ_1 is an $(k \times 1)$ vector of coefficients.

The dynamics of pricing factors (3.1), short rate (3.4), and the pricing kernel (3.3) imply that the price of an n -period bond can be summarised as

$$P_t^{(n)} = \exp(A_n + B_n' X_t), \quad (3.6)$$

where the factor loadings A_n and B_n follow the recursions:

$$A_{n+1} = -\delta_0 + A_n + B_n'(\mu - \Sigma\lambda_0) + \frac{1}{2} B_n' \Sigma \Sigma' B_n, \quad (3.7)$$

$$B_{n+1} = (\Phi - \Sigma\lambda_1)' B_n - \delta_1. \quad (3.8)$$

and yields of n -period zero coupon bonds are an affine function of the pricing vector:

$$y_t^{(n)} = -\frac{\log P_t^{(n)}}{n} = a_n + b_n' X_t, \quad (3.9)$$

where $a_n = -A_n/n$, and $b_n = -B_n/n$.

3.2.2 Excess Returns in Affine No-Arbitrage Model

To estimate the parameters of this structure, we follow a three-step linear regression approach of Adrian et al. (2013) (hereafter ACM) who use excess holding period

returns to estimate the model. The one-period holding return of a bond maturing in n -period is expressed as

$$rx_{t+1}^{(n)} = \ln P_{t+1}^{(n-1)} - \ln P_t^{(n)} - r_t. \quad (3.10)$$

Using equations (3.3) and (3.10) in Equation (3.2) yields

$$1 = E_t[\exp(rx_{t+1}^{(n)} - \frac{1}{2}\lambda_t'\lambda_t - \lambda_t'\Sigma^{-\frac{1}{2}}v_{t+1})]. \quad (3.11)$$

Assuming that $rx_{t+1}^{(n)}$ and v_{t+1} follow a multivariate normal distribution, ACM show

$$E_t[rx_{t+1}^{(n)}] = Cov[rx_{t+1}^{(n)}, v_{t+1}'\Sigma^{-\frac{1}{2}}\lambda_t] - \frac{1}{2}Var_t[rx_{t+1}^{(n)}]. \quad (3.12)$$

Defining

$$\beta_t^{(n)'} = Cov[rx_{t+1}^{(n)}, v_{t+1}']\Sigma^{-1}, \quad (3.13)$$

and using Equation (3.5), we can rewrite Equation (3.12) such that

$$E_t[rx_{t+1}^{(n)}] = \beta_t^{(n)'}[\lambda_0 + \lambda_1 X_t] - \frac{1}{2}Var_t[rx_{t+1}^{(n)}]. \quad (3.14)$$

We then decompose the unexpected excess return into a component coming from shocks in the pricing factors (v_{t+1}) and a remaining term that is conditionally orthogonal. Then using (3.13), the unexpected excess return can be written as

$$rx_{t+1}^{(n)} - E_t[rx_{t+1}^{(n)}] = \beta_t^{(n)'}v_{t+1} + e_{t+1}^{(n)}, \quad (3.15)$$

where the pricing error $e_{t+1}^{(n)}$ is assumed to be conditionally independent and identically distributed (i.i.d) with variance σ^2 .

Assuming $\beta_t = \beta$ for all t , the return generating process is:

$$rx_{t+1}^{(n)} = \beta^{(n)'}(\lambda_0 + \lambda_1 X_t) - \frac{1}{2}(\beta^{(n)'}\Sigma\beta^{(n)} + \sigma^2) + \beta^{(n)'}v_{t+1} + e_{t+1}^{(n)}. \quad (3.16)$$

This specification enables the holding period return to be decomposed into; expected return from previous pricing factors and a part coming from their innovations. Stacking the system across maturities and time period gives

$$rx = \beta'(\lambda_0 \iota'_T + \lambda_1 X_-) - \frac{1}{2}(B^*vec(\Sigma) + \sigma^2 \iota_N)\iota'_T + \beta'V + E, \quad (3.17)$$

where rx denotes an $N \times T$ matrix of excess returns, $\beta = [\beta^{(1)} \beta^{(2)} \dots \beta^{(N)}]$ is a $K \times N$ matrix of factor loadings, ι_T and ι_N are $T \times 1$ and $N \times 1$ vectors of ones, $X_t = [X_0 X_1 \dots X_{T-1}]$ is $K \times T$ matrix of lagged pricing factors. We define $B^* = [vec(\beta^{(1)}\beta^{(1)'}) \dots vec(\beta^{(N)}\beta^{(N)'})]$ ($N \times K^2$), V is factor innovations ($K \times T$), and E is return pricing errors ($N \times T$).

3.2.3 Estimation Methodology

The estimation follows the procedure proposed by ACM using excess returns and observed yield factors. First, we estimate Equation (3.1) using the vector of pricing factors, X_t . This step enables us to obtain the estimate of the transition matrix and obtain estimates of innovations \hat{v}_t . Stacking the estimated factor innovations \hat{v}_t in matrix \hat{V} , we obtain an estimate of the state variable variance-covariance matrix $\hat{\Sigma} = \hat{V}\hat{V}'/T$.

Factorising Equation (3.17) in terms of X and \hat{V} results in

$$rx = \mathbf{a}\iota_T + \mathbf{c}X_- + \boldsymbol{\beta}'\hat{V} + E. \quad (3.18)$$

According to this equation, we regress the monthly excess holding period returns on a constant, pricing factors, and estimated innovations. Least squares regression estimation provides estimates of \mathbf{a} , $\boldsymbol{\beta}$, and \mathbf{c} ($\hat{\mathbf{a}}$, $\hat{\boldsymbol{\beta}}$, and $\hat{\mathbf{c}}$). The estimate of the pricing error covariance matrix is then calculated as $\hat{\sigma}^2 = tr(\hat{E}\hat{E}')/NT$ and B^* is constructed using $\hat{\boldsymbol{\beta}}$.

Finally, the estimates of parameters in the price of risk equation ($\hat{\lambda}_0$ and $\hat{\lambda}_1$) can be obtained using the estimates of the parameters from the previous steps. Arranging Equation (3.17), we know that $\mathbf{a} = \boldsymbol{\beta}'\lambda_0 - \frac{1}{2}(B^*vec(\hat{\Sigma}) + \hat{\sigma}^2\iota_N)$ and $\mathbf{c} = \boldsymbol{\beta}'\lambda_1$. Using the relations, the risk parameters are estimated as

$$\hat{\lambda}_0 = (\hat{\boldsymbol{\beta}}\hat{\boldsymbol{\beta}}')^{-1}\hat{\boldsymbol{\beta}}(\hat{\mathbf{a}} + \frac{1}{2}(\hat{B}^*vec(\hat{\Sigma}) + \hat{\sigma}^2\iota_N)), \quad (3.19)$$

$$\hat{\lambda}_1 = (\hat{\boldsymbol{\beta}}\hat{\boldsymbol{\beta}}')^{-1}\hat{\boldsymbol{\beta}}\hat{\mathbf{c}}. \quad (3.20)$$

The short-term interest rate (Equation (3.4)) are measured with error η_t :

$$r_t = \delta_0 + \delta_1'X_t + \eta_t. \quad (3.21)$$

We use least squares estimation to obtain estimates $\hat{\delta}_0$ and $\hat{\delta}_1$.

From Equation (3.6), log bond prices follow an affine process depending on the vector of pricing factors X_t :

$$\ln P_t^{(n)} = A_n + B_n'X_t. \quad (3.22)$$

Substituting equation (3.22) into Equation (3.10) and matching the terms with the process of Equation (3.16) give the following linear restrictions which can be solved recursively:

$$A_n = A_{n-1} + B'_{n-1}(\mu - \lambda_0) + \frac{1}{2}(B'_{n-1}\Sigma B_{n-1} + \sigma^2) - \delta_0, \quad (3.23)$$

$$B'_n = B'_{n-1}(\Phi - \lambda_1) - \delta'_1, \quad (3.24)$$

$$A_0 = 0, \quad B_0 = 0, \quad \text{and} \quad (3.25)$$

$$\beta^{(n)} = B'_n. \quad (3.26)$$

3.3 Data

3.3.1 Economic Policy Uncertainty

The main variable measuring economic uncertainty in our study is the economic policy uncertainty series developed by Baker et al. (2016) for the United States. This index is constructed by counting the frequency of articles in 10 leading U.S. newspapers containing combinations of terms in three categories: (i) “economic” or “economy”; (ii) “uncertain” or “uncertainty”; and (iii) “Congress,” “deficit,” “Federal Reserve,” “legislation,” “regulation,” or “White House.” The series are available from 1985 on a monthly basis, and extended monthly historical index covers from 1900 for the United States. The latter index is built with expanded article selecting criteria and with different coverage of the newspaper archives. This model-free constructing methodology based on newspaper archives, with the aid of search engine technology, enables it to be extended to most countries and facilitates to build specific sub-categories measures.⁹

Figure (3-1) plots monthly *EPU* ranging from 1985 to 2015 for the US. It spikes apparently around major political and economic events such as the 9/11 terrorist attack in 2001 and the Lehman Brothers collapse in 2008. The index may cover a restrictive area of uncertainty in that it only counts “economic” uncertainty related to “government policy”, but we expect it will have a broad impact on financial markets considering the significant role of government in the overall economy.¹⁰ In the empirical exercise, Baker et al. (2016) show that increases in *EPU* are followed by decreases in overall economic activities like investment, output, and employment. When using firm-level data, it is found that policy sensitive economic sectors (for example, industry with higher exposure to government purchase) respond more drastically to *EPU* changes.

3.3.2 Bond Market Variables

We use daily observations of nominal zero-coupon bond yields from the dataset built by Gürkaynak et al. (2007).¹¹ The interest rate series are constructed using the methodology of Nelson-Siegel-Svensson (Nelson and Siegel 1987; Svensson 1994) and the estimated parameters of daily yield curves are also provided. Based on the model, we back out the daily yields for all the maturities between 3 and 120 months. For the one month risk-free rate, we use the Treasury Bill rate from Ibbotson and Associates.¹² Figure (3-2) plots end-of-month bond yields at selective

⁹Monthly series of economic policy uncertainty for 11 countries are being updated on a monthly basis at <http://www.policyuncertainty.com>. Daily series for the US and the UK are also available since 1985 and 2001, respectively. For more detailed explanation of the index, see Baker et al. (2016).

¹⁰Baker et al. (2016) also provide a broader measure of economic uncertainty, dropping ‘policy’ criteria among the three words combinations. The correlation coefficient of the two series between 1985:01 and 2015:12 is 0.88.

¹¹The data-set is updated periodically and accessible at the Federal Reserve Board Website (<https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html>).

maturities ranging from 12 to 120-month.

We denote $p_t^{(n)}$ the log price of an n -month zero-coupon bond at time t . Then, the log return from buying an n -month bond at time t and selling it as a $(n - h)$ -month bond at time $t + h$ becomes

$$r_{t+h}^{(n)} = p_{t+h}^{(n-h)} - p_t^{(n)}, \quad (3.27)$$

where h is the holding periods in months. We can express excess log returns as

$$rx_{t+h}^{(n)} = r_{t+h}^{(n)} - y_t^{(h)}, \quad (3.28)$$

where $y_t^{(h)}$ is the h -period zero-coupon rate at time t . We then calculate excess bond returns from 1 to 12-month investment horizons. Figure (3-3) illustrates monthly excess returns for the 1, 3, 5, and 10-year maturities. Table (3.1) reports summary statistics for annualised monthly excess returns. The means and standard deviations of the monthly returns increase as maturity increases and as the holding period decreases. Our return forecasting exercises using *EPU* and other return forecasting factors are based on the sample beginning January 1985, when the main *EPU* index starts, and ends in December 2015.

3.3.3 Other Variables

We consider two well established return forecasting factors in the literature (Cochrane and Piazzesi 2005, 2008; Cieslak and Povala 2015) as control variables in the return forecasting exercise. Cochrane and Piazzesi's factors for each holding period

¹²The rate is accessible at Kenneth French's website (<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>).

is constructed by regressing excess returns across maturities on the one-year yield and forward rates:

$$rx_{t+12}^{(n)} = \gamma_0^{(n)} + \gamma^{(n)} F_t + \eta_{t+12}^{(n)}, \quad (3.29)$$

where F_t is the vector of ten one-year forward rates. As in Cochrane and Piazzesi (2008), we calculate the *CP* factor to be the first principal component of the expected excess returns.

The Cieslak and Povala's factor is built by decomposing the yields into the expectation hypothesis components and the term related to risk premia. Specifically, the return forecasting factor is the fitted value from regressing the average of bond excess returns on the maturity-specific yield cycles:

$$\overline{rx}_{t+h} = \delta_0 + \delta_1 \bar{c}_t + \delta_2 c_t^{(1)} + u_{t+h}, \quad (3.30)$$

where $c_t^{(i)}$ is i maturity-specific yield cycle, obtained by projecting i -year maturity yields with different maturities on trend inflation measured by a discounted moving average of core inflation. \bar{c}_t is the average of the cycle for 2 to 20-year maturity. We call the resulting forecasting factor as *Cycle*.

We also include general macroeconomic and financial uncertainty proxies used in recent studies, in order to confirm whether *EPU* keep its forecasting power controlling for the other uncertainty measure. Macroeconomic uncertainty (*MacroU*, hereafter) of Jurado et al. (2015) is built on the dispersion of forecast errors based on a statistical model using a large number of macroeconomic and financial variables. The financial uncertainty measure (*FinU*) is introduced by Ludvigson et al. (2017) using the similar methodology of Jurado et al. (2015) with an extensive financial dataset. Analysing the possible contemporaneous effects between the two

types of uncertainty and economic activity, Ludvigson et al. (2017) suggest that financial uncertainty primarily works as exogenous shocks affecting business cycles fluctuations, while uncertainty about real economic activity is close to the endogenous consequence of adverse macroeconomic shocks.

Table (3.2) presents the correlation coefficients between three yield factors, the return forecasters, and two additional uncertainty measures for the sample period between 1985:01 and 2015:12. The correlation structure shows *EPU* and other statistical uncertainty measures are positively related (around 0.3 with *MacroU* and 0.4 with *FinU*). *EPU* has negative correlation with Cieslak and Povala's *Cycle* factor, and has no significant correlation with *CP* factor.

3.4 Policy Uncertainty and Bond Returns

3.4.1 Return Predictability of Economic Policy Uncertainty

We first examine the forecasting ability of *EPU* for future Treasury excess return for different maturities across various holding periods. To test whether *EPU* contains information that is not captured by the current bond prices, we add it to a prediction equation of excess bond returns for different maturities and different holding period to the yield factors representing the information in the current yield curve. Specifically, we estimate

$$rx_{t+h}^{(n)} = \beta_0^{(n)} + \beta_1^{(n)} PC_t + \beta_2^{(n)} EPU_t + \varepsilon_{t+h}^{(n)}, \quad (3.31)$$

where $PC_t = (PC1_t \ PC2_t \ PC3_t)'$ and EPU_t is economic policy uncertainty at time t .¹³ Joslin et al. (2014) and Bauer and Hamilton (2017)'s return forecasting exercises include the first three principal components (PC s) of the yield curve - level, slope, and curvature - which explain most of all the cross-sectional variations in the yield curve (Litterman and Scheinkman 1991). All the dependant variables in the regression are standardised to have mean 0 and a standard deviation of 1 to facilitate the interpretation of the coefficients. The Newey and West (1987) t -statistics with the optimal lag length determined following Newey and West (1994) are reported in parentheses.

The regression results are presented in Table (3.3). As shown in previous studies such as Bauer and Hamilton (2017), $PC1$ (level) and $PC2$ (slope) significantly predicts bond excess returns consistently across most maturities and holding periods. We find that the addition of EPU predicts the existence of positive excess returns. Adding EPU in addition to the first three principal components of yields increases the adjusted R^2 , implying that EPU contains predictive information for future bond returns that is not spanned by contemporaneous yields. We calculate that a one standard deviation increase in the EPU predicts a significant positive future excess return from 0.48% (1-year maturity, annualised) to 1.97% (5-year maturity) when the holding period is a month.

The size and significance of these effects are larger in near investment horizons, having no statistically significant influence in 12-month investment horizons. Our interpretation of this results is that EPU is more closely related to bond price current/immediate volatility affecting investment decisions with short horizons.¹⁴

¹³The value of EPU for January 2000 is used for forecasting the one-month log excess returns buying n -month bond on 31st January 2000 and selling it as a $(n - 1)$ -month bond on 29th February 2000.

¹⁴The finding is in line with Brogaard and Detzel (2015)'s empirical work using stock returns

To further establish the validity of *EPU* as an independent forecasting factor, we add it as a predictor to the augmented model estimated by ACM which adds two additional *PCs* (*PC4* and *PC5*) extracted from the observed term structure. The test for the significance of *EPU* in the augmented model will help establish whether the *EPU* is simply a substitute of the two additional components or it makes an independent contribution. Table (3.4) reports that *PC5* affects bond returns negatively. However, the size of coefficients and their statistical significance of *EPU* do not diminish, confirming that the predictability of *EPU* is independent of those from current term structure of interest rates.

3.4.2 Predictability Controlling Other Return Forecasters

To test whether *EPU* forecasts the future bond return in the presence of additional forecasting factors, we add the factors of Cochrane and Piazzesi (2005, 2008) and Cieslak and Povala (2015) in Equation (3.31) as follows:

$$rx_{t+h}^{(n)} = \beta_0^{(n)} + \beta_1^{(n)} PC_t + \beta_2^{(n)} EPU_t + \beta_3^{(n)} X_t + \varepsilon_{t+h}^{(n)}, \quad (3.32)$$

where X_t includes the *CP* and *Cycle* factors introduced in Section (3.3).

Columns (1) and (2) of Table (3.5) and Table (3.6) report the regression coefficients for bond excess returns with 1 and 3-month holding periods. Both *CP* and *Cycle* factors predict with positive one-month holding period returns across all the maturities ranging from 1 to 10 years. Controlling for *CP* and *Cycle* factor, it is shown that *EPU* consistently holds significant predictive power for excess returns

that the increase in *EPU* raises expected excess returns. The statistical significance of the effects on stock returns is larger than our results using Treasury bond returns, but the predictability for stock return is more concentrated on 2 to 3 month holding periods.

of 1 to 3-year maturity at the 1% significance level. Its statistical significance deteriorates as the maturity increases, keeping its significance just below 10% level for 10-year maturity. As reported in Table (3.6), regressions for excess returns with longer holding periods show limited predictability of *EPU*, displaying no significant relations for 3-month holding excess returns over 5-year maturities. However, as reported in Table (3.7) and (3.8), we can confirm that the predictive power of *EPU* factor holds for all the maturities with 1-month holding period and for 1 and 2-year maturity with 3-month holding period, even controlling for all the return forecasting factors considered.

We test the validity of the model incorporating *CP* and *EPU* to the augmented 5*PC* model by using a simple model specification test proposed by Davidson and MacKinnon (1981, 1993).¹⁵ Specifically, we compare two non-nested models, both of which have five return forecasting factors, but the first model (*M1*) uses the first five *PCs* of interest rates, whilst the other model (*M2*) has factors comprising the first three *PCs*, *CP*, and *EPU*. Table (3.9) presents the *J*-test results comparing the two models forecasting bond excess returns for 1-month holding period. Panel A presents the fitted values from *M1* ($\widehat{r\hat{x}}_{M1t+1}^{(n)}$) do not significantly forecast returns when added in *M2*. As shown in Panel B, the fitted values from *M2* ($\widehat{r\hat{x}}_{M2t+1}^{(n)}$) enter significantly in the regressions for all the maturities rendering strong support for the model using *CP* and *EPU* as bond return predictors.

Having established the statistical improvement over the five *PC* factor model, we now proceed to test whether the newly established variables proxying economic and financial uncertainty are substitutes for the presence of *EPU* as a forecasting driver. Specifically, we consider the same regressions (Equation (3.31)) adding two

¹⁵Davidson and MacKinnon (1981, 1993)'s *J*-test examines the validity of two non-nested models. The basic idea of the test is that the fitted values from *M1* (*M2*) have no explanatory power when they added to *M2* (*M1*), if the other model is the correct one.

uncertainty measures as:

$$rx_{t+h}^{(n)} = \beta_0^{(n)} + \beta_1^{(n)} PC_t + \beta_2^{(n)} EPU_t + \beta_3^{(n)} U_t + \varepsilon_{t+h}^{(n)}, \quad (3.33)$$

where U_t are two statistical uncertainty measures (*MacroU* and *FinU*) discussed in Section (3.3). Columns (3) of Table (3.5) and Table (3.6) reports *MacroU* and *FinU* positively affect one-month excess return, but the significance of the predictive power is somewhat limited. Meanwhile, *EPU* consistently holds significant coefficients for the returns of short maturity bonds when controlling the two uncertainty measures. From an unreported exercise, we find that both *MacroU* and *FinU* predict significant positive bond excess returns in the absence of *EPU* as a factor in the regression.¹⁶ These results suggest that *EPU* captures economic uncertainty which is related to but distinct from other macroeconomic and financial uncertainty variables, working as an independent factor forecasting returns.

From this section, we conclude that the significance profile of *EPU* as a predictor of excess returns remains approximately constant independently of the conditioning set.¹⁷ *EPU* is a strong predictor for 1-month holding period for up to medium maturity bonds, subsequently its significance across maturities is restricted to short-term bonds as the holding horizon increases. The addition of

¹⁶As reported, the two alternative uncertainty measures lose its predictive power in the regression with *EPU* factor. The coefficients on *MacroU*, however, become significant when the holding period increases. This result and the strong comovement of *EPU* with *FinU* imply that the *EPU* measure is likely to be linked to the type of uncertainty that affects financial market.

¹⁷The economic gains from using the predictability of bond excess returns (relative to the no-predictability alternative consistent with the expectation hypothesis) have been tested in a few previous studies. For example, Thornton and Valente (2012) have found that the predictive models based on forward spreads (Fama and Bliss 1987) or the term structure of forward rates (Cochrane and Piazzesi 2005) are not necessarily connected to economic gains in investment. This disparity between the return forecastability and the factors failure generating economic gains are under active exploration. Gargano et al. (2017), for instance, have shown that a three factor model incorporating a macro factor of Ludvigson and Ng (2009) into the two forecasting factors tested by Thornton and Valente (2012) produces noticeable gains in out-of-sample forecast accuracy.

alternative uncertainty proxies and the well established forecasting factors such as *CP* and *Cycle* does not change this profile, establishing *EPU*'s independent contribution as a forecasting factor for short-term forecasting horizon.

3.5 Economic Policy Uncertainty in ATSM

The finding from previous excess return forecasting exercise implies that using only principal components from the yield curve will omit significant information contained in macroeconomic proxies for uncertainty such as *EPU*. In this section we test for the contribution of *EPU* in the pricing kernel (Equation (3.3)) under alternative conditioning factor structure.

By and large traditional models of accounting for the pricing kernel are functions of the observed yield curve, via the constructed *PCs*. The objective of this section is to examine whether the substitution of some of the *PCs* by variables outside the yield curve can be used for both description of the pricing kernel and the term premium in particular.

Yield on n -month bond $y_t^{(n)}$ satisfies the following identity:

$$y_t^{(n)} = \frac{1}{n} \sum_{\tau=0}^{n-1} E_t[y_{t+\tau}^{(1)}] + tp_t^{(n)}, \quad (3.34)$$

where, $y_t^{(1)}$ is risk-free nominal short rate and $tp_t^{(n)}$ is the nominal term premium on n -month bond. The average expected risk-free short rate over the maturity is the expectation component of the n -month bond which correspond to the yield following the expectation hypothesis. The second term representing the risk premium can be expressed using the expected excess holding return $rx_{t+1}^{(n)}$ as

$$tp_t^{(n)} = \frac{1}{n} \sum_{\tau=0}^{n-1} E_t[rx_{t+\tau+1}^{(n-\tau)}]. \quad (3.35)$$

Accurate estimates of this quantity require that the conditioning information set reflects all relevant information, not restricting it to the existing term structure. Following the expectation hypothesis, we calculate the yield by setting the parameters of the price of risk (λ_0 and λ_1). Then the term premia implied by the model can be obtained by differencing the fitted yields and the expected terms for each maturity bond.

To summarise, an affine model of the term structure aims at providing efficient estimates of the price of risk. If the price of risk is indeed zero, the stochastic discount factor depends the instantaneous interest rate alone. In the presence of positive price of risk, the conditioning factors provide such estimates. It is therefore important that the set of the conditioning factors contains all the relevant information affecting both components constituting the observed yields; the expectations and the term premia.

The calculation of the price of risk is based upon forecasts of the factors rather than information contained in the observed yield curves (see Equations (3.19) and (3.20)). Fitting models accounting for the pricing kernel based exclusively on PCs does not take into account that it is the forecast of the factors that determines the price of risk rather than the existing extracted principal components. To take this into account, we introduce affine models, based on 5 factors consisting of the traditional yield factors along with *CP* and *EPU*. These two factors are not extracted from the observed yield curves and the forecasts will determine the price of the risk and the term premia.

By including additional factors such as the *EPU*, we test for their distinct

contribution to the dynamics of both the term premium and the formation of expectations. The empirical evidence to date in accounting for the yields suggests that the 5-factor *PC* model is superior to the traditional 3-factor *PC* model with the addition to *CP* factor. Our findings in forecasting bond returns from the Section (3.4), in conjunction with Equation (3.35), imply that there is a distinct case for substituting some of the principal components by variables generated outside the yield curve. To explain the fluctuations in yields, we need to calculate both expectations and term premia. Estimating term premia requires predicting future returns which can be better forecasted by the additional factors such as *CP* and *EPU*.

To account for the yields in accordance with the evidence presented in Section (3.4) we need principal components and some forecasting variables. If we were to restrict the overall number of factors to five then we consider two affine models, one using three *PCs* and *CP* and *EPU*, and one with 5 factors used by ACM. We call the former five factor specification as the “Yield-Plus” model, since the factors from the yield curve are augmented by the additional data containing yield-independent information. Our pricing factor vector is $X_t = [PC1_t \ PC2_t \ PC3_t \ CP_t \ EPU_t]'$, where CP_t is the Cochrane and Piazzesi (2005)’s return forecasting factor and *EPU* is the economic policy uncertainty index of Baker et al. (2016).¹⁸

The sample for model estimation begins in January 1962 from when Gürkaynak et al. (2007)’s zero-coupon yield series and ends in December 2013. ACM include the forth and fifth principal components of the yield curve which have significant role in explaining expected excess returns, although they do not explain much

¹⁸Principal components of the yield curve are extracted from the yields with maturities $n = 3, 6, \dots, 120$ months. To back out interest rates with various maturities, the parameters for Nelson-Siegel-Sevenson (1994) yield curves, also provided by Gürkaynak et al. (2007), are used. We choose end-of-month values for monthly frequency estimation.

about the contemporaneous yield curve. Due to the short span of the main *EPU* index, we choose the historical news-based policy index of Baker et al. (2016) which is available on a monthly basis.¹⁹ As introduced in Section (3.3), Cochrane and Piazzesi (2005, 2008) build the return forecasting factor using annual excess holding period returns as the dependent variable. Our corresponding factor is the first principal component of expected returns obtained by regressing the 1-month holding period returns ($rx_{t+1}^{(n)}$) on ten one-year forward rates. Estimation using monthly excess returns is required because the regression Equation (3.18) holds explicitly for non-overlapping monthly returns.

Figure (3-4) shows the observed (solid lines) and estimated yields (dotted lines) for 12, 60, and 120-month Treasury notes, indicating that the two series for each maturity are almost indistinguishable. In estimating Equation (3.18), the cross-equation constraints (Equations (3.24) and (3.25)) are not imposed. In deriving the predicted values of yield curve, the constraints on factor loading are used. These are derived after we obtain the estimates of all the parameters from the excess returns regressions. The dashed lines in Figure (3-4) plot the term premia estimates of the model and the dashed lines in Figure (3-5) show that the expected component of excess returns explains a considerable amount of the variations in observed series, capturing the highly volatile movements in excess returns.

As shown in the lower panel of Figure (3-6), *CP* (dash-dotted line) and *EPU* (thicker dashed line) factors forecast positive excess returns, in line with the estimation results in the previous section. The loadings on the first three principal, illustrated in the upper panel, confirm the factors' role of the level, slope, and

¹⁹To build longer span *EPU* index, Baker et al. (2016) use digital archives of six newspapers and apply expanded word combinations also related to policy-related economic uncertainty. The historical *EPU* series covers the period 1900:01 and 2014:10 and moves closely together with the main monthly *EPU* covering after 1985:01. The correlation coefficient between the two series for the overlapping period is 0.98.

curvature of the yield curve accounting for the observed term structure. In the case of expected excess returns we find that the influence of three *PCs* is minimal, reinforcing the importance of *CP* and *EPU* as the factors predicting excess returns. The loading on the *CP* factor for excess returns increases with maturity, whilst the influence of *EPU* peaks between 60 and 80 months. From this result, we can infer that the effect of monetary easing to counter the adverse impact of the economic shocks can be offset partly by the influence from the changing term premia. This implies that during times of high economic uncertainty, monetary authorities have to act aggressively and try to mitigate the uncertainty in policies to stabilise the economy.

To access the significance of the factors' effects on excess returns, in Figure (3-7), we report 90% confidence intervals (dashed lines) for the factor loadings ($\beta'\lambda_1$), computed using a bootstrap procedure introduced by Malik and Meldrum (2016) with 10,000 replications. Specifically, we generate a bootstrap sample by using the estimated parameters from the initial estimation and randomly selected estimated residuals for v_t , E , and η_t in Equations (3.1), (3.18), and (3.21). We re-estimate the model using the bootstrapped sample and obtain confidence intervals by computing the percentiles of the bootstrapped estimates. The result shows that *CP* factor is significant for all the maturities, whilst *EPU* factor is significant up to around 7 years, which is consistent with our findings in the return forecasting exercises that the predictive ability of *EPU* are more pronounced in short- and medium-term maturities.

To compare the approach with a model incorporating only the factors summarising yield curve, we estimate a model with the first five principal components, which we call "Yield-Only" model. Scheinkman and Litterman (1991) show that almost all the variations of the yield curve can be explained by three factors, whilst

Cochrane and Piazzesi (2005, 2008) and Duffee (2011) find that including additional factors, which are not important for explaining variations of current yield, can be essential for explaining expected returns.

Figure (3-8) shows the observed (solid lines) and estimated yields (dotted lines) for 12, 60, and 120-month Treasury notes, indicating that estimated yields are almost identical to the actual yields. The observed and fitted excess holding returns are illustrated in Figure (3-9) showing that the fitted returns (dotted lines) follows the actual returns (solid lines) closely.

As discussed in ACM, the bottom panel of Figure (3-10) shows that the second (dashed line), fourth (dash-dotted line), and fifth (thicker dashed line) principal components play important roles explaining excess returns, whilst the weights on yields associated with the fourth and fifth factors are negligible. 90% confidence intervals (dashed lines) for the factor loadings, computed using the same bootstrap procedure with 10,000 replications, are reported in Figure (3-11). The influence of $PC2$ and $PC4$ is stronger than the other PC s and is shown to have significance for most maturities, whilst $PC1$ and $PC5$ are significant only in some maturities. Comparing the effects of the yield factors on excess returns with those of CP and EPU factors (shown in Figure (3-7)) suggests that the predictive content of CP factor is possibly related with the second, fourth, and fifth principal components. The correlation coefficients between CP and $PC2$, $PC4$, and $PC5$ are 0.53, 0.42, and 0.21, respectively. Meanwhile, the effect of EPU factor seems to be less related with those from principal components, as correlations with the three PC s are 0.36, 0.24, and 0.07, respectively.

Figure (3-12) compares the expected excess return using the two models: the Yield-Only ($5PC$) and the Yield-Plus model ($3PC$, CP , and EPU). The left panel

presents the observed excess returns with maturities of 12, 60, and 120 months and the right panel plots expected parts of excess returns predicted by the two models. The expected returns implied by Yield-Plus model fluctuate more closely with the actual excess returns, confirming the two factors predictive power established in the previous section.

From Tables (3.10) and (3.11), the average of calculated pricing errors do not exceed 11 basis points with equivalent standard deviations for short maturities. These pricing errors become vanishingly small along with standard deviations, as maturities increase. In terms of returns, in all cases the mean error is less than 4 basis points with standard deviation between 6 and 42 basis points.

As we do not observe major differences in statistical fits, we expect more realistic estimate of term premia from the first model as it includes in the specification forecasts of variables independent of the observed yields. Although the second model may provide better statistical fit for the observed yields, it does not account for the forecasting errors of the hidden factors that determine term premia. From the results above we conclude that, given the very small magnitude of pricing errors in all cases, the advantage of calculating the price of risk by using estimates of hidden factors outweighs the very small losses of statistical fit. We then calculate the term premia from the two models, one using information only from the term structure and the alternative which includes only the 3 first *PCs* with the *CP* and *EPU* as hidden factors.

The left column of Figure (3-13) plots the expected yields and term premia with observed yields for maturity 12, 60, and 120, implied by Yield-Plus model which include three *PCs*, *EPU*, and *CP*. The right column plots those of Yields-Only model. The dashed lines indicate expected yields, while the solid lines below show

the variations in term premia. It is natural that lower-maturity yields move more closely with the expected term, and the share of implied term premia in observed yields increases along with maturity. The two components estimated by the two models show broadly similar movements.

Figure (3-14) compares the term premia estimates from the two models. From the left column of the figure, we can see that the term premia estimates (dashed lines) by Yield-Plus approach have higher volatility, contributing more to the variations in observed yields. This finding over the important role of the term premia in explaining the actual yields dynamics is consistent with the results in recent studies (see, for example, Bernanke et al. 2004; Dewachter et al. 2014; Crump et al. 2017), which attribute more prominent role of the term premia accounting for variation in yield curve dynamics.

Theoretical models with utility maximising agents predict that investors demand higher risk premium under bad economic condition (see, for example, Campbell and Cochrane 1999; Bansal and Yaron 2004; Wachter 2006; Bansal and Shaliastovich 2013). For example, in the model of Wachter (2006), short-term real rate is negatively correlated with surplus consumption (current consumption compared to its recent trend), as agents wish to borrow more in order to smooth consumption when current consumption is temporally reduced by negative economic shocks. This intertemporal consumption smoothing due to habit persistence makes agents demand additional compensation to hold bonds, implying that term premia should exhibit countercyclical movements as reported in much empirical literature (Harvey 1989; Cochrane and Piazzesi 2005, among others).²⁰

²⁰The relation between consumption shocks and short-term rates is dependent upon the relative size of effects between agents' desire for consumption smoothing and precautionary saving. Wachter (2006)'s calibration result supports the dominance of the smoothing effect, consistently with the countercyclical pattern of term premia in the empirical studies.

We examine the cyclical variations of our estimated term premia whether they satisfy the theoretical prediction. Figure (3-15) compare the 12-month moving averages of estimated term premia with 60-month maturity and industrial production (IP_t) growth. Both of the term premia increase as IP_t growth deteriorates and decrease as growth rises, suggesting both model produce countercyclical term premia. Furthermore, the negative correlation between tp_t and IP_t growth is stronger for the *Yield-Plus* model (-0.15) compared to the correlation from the *Yield-Only* model (-0.11).²¹ As shown in the third plot of Figure (3-15), we find strong negative relation between the gap of the two term premia estimates (*Yield-Plus* – *Yield-Only*) and IP_t , with correlation of -0.33 , suggesting that the difference between the two term premia is closely related to the cyclical fluctuations in economic activity.

3.6 Conclusion

We provide strong empirical evidence of the predictive ability of uncertainty in government policies (EPU) for future bond returns. EPU has been shown to contain information predicting future returns that is not spanned by the factors in the contemporaneous term structure. The size and significance of the effects is especially large for short maturity bonds in near investment horizons.

We have shown that, incorporating EPU as an additional pricing factor in affine term structure models does not explain variations in current yields much, but it affects the term premia by influencing the price of risk. Model predicted term

²¹We also confirm that the countercyclical relation between IP_t and TP_t and the stronger negative correlations for *Yield-Plus* model hold for other maturities and in estimations using sub-sample periods. Alternative measures of economic activity such as ADS real-time Business Conditions Index (Aruaba, Diebold, and Scotti 2009) also validate the strong relation.

premia exhibit fluctuations that follow closely the variations in observed yields. These term premia estimates show stronger counter-cyclical movements than those estimates using a model with only yield curve factors. This provides an account for the requirement of increasing risk compensation under adverse economic conditions as theories expect, independently of the shape and position of the yield curve.

Table 3.1: Treasury Bond Excess Returns

	1y	2y	3y	5y	7y	10y
<i>1-month holding period</i>						
Mean	0.994	1.798	2.529	3.783	4.779	5.916
Median	0.489	1.368	2.239	4.417	4.629	6.502
Max	12.099	25.451	38.683	65.813	96.327	148.694
Min	-7.901	-18.740	-27.804	-48.865	-76.969	-117.932
Std. Dev.	2.789	6.605	10.549	18.037	24.979	34.844
Skewness	0.705	0.193	0.020	-0.046	0.031	0.146
Kurtosis	4.969	3.756	3.380	3.373	3.771	4.512
AC(1)	0.174	0.167	0.144	0.101	0.066	0.031
AC(5)	0.011	-0.022	-0.049	-0.072	-0.076	-0.075
<i>3-month holding period</i>						
Mean	0.673	1.501	2.255	3.553	4.596	5.800
Median	0.266	0.888	1.474	2.445	3.359	4.513
Max	6.694	14.486	20.600	33.300	45.319	70.066
Min	-3.148	-9.664	-16.109	-27.289	-36.663	-48.338
Std. Dev.	1.569	3.984	6.373	10.661	14.375	19.433
Skewness	0.837	0.456	0.329	0.217	0.191	0.245
Kurtosis	4.008	3.445	3.184	2.945	3.030	3.468
AC(1)	0.759	0.740	0.724	0.701	0.681	0.661
AC(5)	0.149	0.026	-0.036	-0.073	-0.063	-0.038
<i>6-month holding period</i>						
Mean	0.439	1.263	2.014	3.311	4.354	5.553
Median	0.238	0.941	1.598	2.645	3.859	4.870
Max	2.837	8.182	14.242	25.546	38.511	59.128
Min	-1.141	-4.603	-8.866	-17.136	-24.822	-35.416
Std. Dev.	0.808	2.544	4.222	7.224	9.849	13.442
Skewness	0.679	0.340	0.238	0.173	0.154	0.196
Kurtosis	2.877	2.748	2.822	2.926	3.106	3.558
AC(1)	0.888	0.871	0.856	0.839	0.828	0.817
AC(5)	0.381	0.266	0.186	0.115	0.100	0.103
<i>12-month holding period</i>						
Mean		0.824	1.575	3.777	3.938	5.154
Median		0.634	1.322	3.930	4.193	5.605
Max		4.194	8.663	24.918	26.361	39.212
Min		-2.522	-4.972	-11.248	-11.807	-16.410
Std. Dev.		1.311	2.513	6.067	6.355	8.848
Skewness		0.230	0.126	0.165	0.176	0.307
Kurtosis		2.558	2.760	3.374	3.424	3.859
AC(1)		0.948	0.938	0.914	0.912	0.902
AC(5)		0.651	0.601	0.498	0.493	0.463

Notes: This table reports summary statistics for annualised Treasury bond excess returns (in percentage) with four different holding period (1, 3, 6, 12 months). Each panel includes bond excess returns for 1 to 10-year bond maturities. Excess returns are constructed using daily Treasury yield curve constructed by Gurkaynak et al. (2007) and Treasury bill rate from Ibbotson and Associates. The sample period covers from 1985:01 to 2015:12.

Table 3.2: Correlation Coefficients of Predictor Variables

	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	<i>EPU</i>	<i>CP</i>	<i>Cycle</i>	<i>MacroU</i>	<i>FinU</i>
<i>PC1</i>	1.000							
	-							
<i>PC2</i>	0.002 (0.036)	1.000						
		-						
<i>PC3</i>	-0.007 (-0.125)	0.003 (0.053)	1.000					
			-					
<i>EPU</i>	-0.361 (-7.432)	-0.256 (-5.093)	0.332 (6.753)	1.000				
			-					
<i>CP</i>	0.304 (6.120)	-0.563 (-13.088)	0.183 (3.567)	0.038 (0.721)	1.000			
				-				
<i>Cycle</i>	0.477 (10.439)	-0.522 (-11.762)	-0.264 (-5.263)	-0.219 (-4.318)	0.441 (9.442)	1.000		
					-			
<i>MacroU</i>	-0.236 (-4.659)	-0.035 (-0.679)	0.295 (5.932)	0.316 (6.390)	0.194 (3.800)	-0.089 (-1.718)	1.000	
						-		
<i>FinU</i>	-0.090 (-1.726)	-0.119 (-2.303)	0.253 (5.021)	0.411 (8.673)	0.171 (3.334)	0.069 (1.330)	0.641 (16.043)	1.000
							-	

Notes: This table reports the correlation coefficients for the three yield factors (*PC1*, *PC2*, and *PC3*), economic policy uncertainty of Baker et al. (2016), *EPU*, Cocrane and Piazzesi (2005) factor, *CP*, the cycle factor from Cieslak and Povala (2015), *Cycle*, macroeconomic and financial uncertainty measures by Ludvigson et al. (2017), *MacroU* and *FinU*, respectively. The sample period covers from 1985:01 to 2015:12.

Table 3.3: *EPU* Return Predictability

	1y		2y		3y		5y		7y		10y	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
<i>1-month holding period</i>												
<i>PC1</i>	0.582 (3.854)	0.754 (5.168)	0.883 (2.582)	1.252 (3.627)	1.122 (2.028)	1.644 (2.789)	1.526 (1.549)	2.234 (2.176)	1.867 (1.326)	2.634 (1.924)	2.362 (1.163)	3.124 (1.620)
<i>PC2</i>	-0.327 (-2.212)	-0.204 (-1.361)	-0.858 (-2.371)	-0.595 (-1.600)	-1.407 (-2.392)	-1.034 (-1.700)	-2.489 (-2.532)	-1.983 (-1.995)	-3.485 (-2.696)	-2.937 (-2.401)	-4.765 (-2.819)	-4.220 (-2.767)
<i>PC3</i>	0.126 (0.679)	-0.033 (-0.179)	0.069 (0.167)	-0.271 (-0.650)	0.051 (0.077)	-0.431 (-0.652)	0.341 (0.295)	-0.312 (-0.266)	0.991 (0.588)	0.283 (0.163)	2.120 (0.859)	1.415 (0.566)
<i>EPU</i>		0.479 (3.429)		1.026 (2.835)		1.452 (2.349)		1.971 (1.909)		2.135 (1.624)		2.124 (1.176)
<i>R</i> ²	0.051	0.069	0.027	0.041	0.021	0.032	0.019	0.024	0.019	0.021	0.019	0.019
<i>3-month holding period</i>												
<i>PC1</i>	0.494 (3.436)	0.608 (5.041)	0.855 (2.481)	1.049 (3.081)	1.137 (2.180)	1.353 (2.612)	1.600 (1.806)	1.804 (2.046)	1.990 (1.543)	2.135 (1.670)	2.541 (1.318)	2.544 (1.539)
<i>PC2</i>	-0.295 (-2.012)	-0.214 (-1.467)	-0.807 (-2.154)	-0.668 (-1.700)	-1.352 (-2.318)	-1.197 (-1.910)	-2.449 (-2.679)	-2.303 (-2.313)	-3.468 (-3.002)	-3.364 (-2.668)	-4.779 (-3.318)	-4.776 (-2.960)
<i>PC3</i>	0.022 (0.169)	-0.083 (-0.577)	-0.179 (-0.577)	-0.359 (-1.185)	-0.418 (-0.892)	-0.619 (-1.370)	-0.658 (-0.900)	-0.846 (-1.192)	-0.545 (-0.561)	-0.680 (-0.730)	-0.104 (-0.078)	-0.108 (-0.078)
<i>EPU</i>		0.317 (3.151)		0.540 (1.637)		0.605 (1.064)		0.567 (0.592)		0.406 (0.332)		0.010 (0.008)
<i>R</i> ²	0.126	0.153	0.082	0.092	0.074	0.078	0.072	0.071	0.071	0.069	0.070	0.067
<i>6-month holding period</i>												
<i>PC1</i>	0.307 (2.391)	0.355 (2.882)	0.645 (1.742)	0.743 (1.943)	0.881 (1.635)	0.972 (1.664)	1.264 (1.513)	1.267 (1.396)	1.599 (1.364)	1.461 (1.181)	2.088 (1.185)	1.699 (0.951)
<i>PC2</i>	-0.152 (-1.175)	-0.116 (-0.936)	-0.586 (-1.402)	-0.513 (-1.310)	-1.101 (-1.673)	-1.031 (-1.600)	-2.193 (-2.245)	-2.192 (-2.246)	-3.249 (-2.759)	-3.353 (-2.820)	-4.648 (-3.179)	-4.941 (-3.452)
<i>PC3</i>	0.015 (0.183)	-0.033 (-0.456)	-0.140 (-0.431)	-0.239 (-0.989)	-0.377 (-0.756)	-0.469 (-1.186)	-0.728 (-1.080)	-0.730 (-1.205)	-0.835 (-1.050)	-0.696 (-0.911)	-0.784 (-0.792)	-0.391 (-0.411)
<i>EPU</i>		0.139 (2.191)		0.283 (1.195)		0.266 (0.662)		0.006 (0.011)		-0.398 (-0.582)		-1.126 (-1.316)
<i>R</i> ²	0.169	0.188	0.113	0.119	0.113	0.114	0.127	0.125	0.137	0.136	0.141	0.144
<i>12-month holding period</i>												
<i>PC1</i>			0.411 (2.394)	0.485 (2.370)	0.633 (2.140)	0.743 (2.121)	1.138 (1.631)	1.155 (1.514)	1.175 (1.602)	1.176 (1.473)	1.514 (1.303)	1.361 (0.787)
<i>PC2</i>			-0.222 (-0.787)	-0.166 (-0.567)	-0.580 (-1.113)	-0.495 (-0.950)	-2.325 (-2.270)	-2.312 (-2.240)	-2.492 (-2.357)	-2.492 (-2.331)	-3.924 (-3.568)	-4.043 (-2.405)
<i>PC3</i>			0.063 (0.334)	-0.014 (-0.079)	0.047 (0.130)	-0.068 (-0.197)	-0.016 (-0.022)	-0.033 (-0.043)	-0.016 (-0.022)	-0.017 (-0.021)	-0.040 (-0.043)	0.121 (0.112)
<i>EPU</i>				0.216 (1.513)		0.322 (1.202)		0.050 (0.090)		0.002 (0.003)		-0.452 (-0.569)
<i>R</i> ²			0.114	0.131	0.106	0.115	0.176	0.173	0.182	0.179	0.221	0.221

Notes: This table reports the coefficient estimates in a regression of the annualised bond excess returns on six n -month maturity bond ranging 12 to 120-month, with a holding period of 1 month. *EPU* is economic policy uncertainty index of Baker et al. (2016). *PCs* are the first three principal components of Treasury yields representing the level, slope, and curvature of yield curve. All the dependant variables in the regression are standardised to have a mean of 0 and a standard deviation of 1. The values in parentheses are the Newey and West (1987) t -statistics with the optimal length determined based on Newey and West (1994). The sample period covers from 1985:01 to 2015:12.

Table 3.4: *EPU* Return Predictability

	1y		2y		3y		5y		7y		10y	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
<i>1-month holding period</i>												
<i>PC1</i>	0.580 (3.971)	0.772 (5.816)	0.878 (2.638)	1.298 (3.893)	0.887 (1.434)	1.721 (2.853)	1.508 (1.513)	2.371 (2.220)	1.844 (1.330)	2.807 (2.000)	2.338 (1.243)	3.299 (1.692)
<i>PC2</i>	-0.326 (-2.282)	-0.188 (-1.332)	-0.856 (-2.555)	-0.555 (-1.593)	0.571 (0.752)	-0.966 (-1.632)	-2.482 (-2.577)	-1.863 (-1.899)	-3.475 (-2.753)	-2.785 (-2.300)	-4.754 (-3.088)	-4.066 (-2.698)
<i>PC3</i>	0.123 (0.648)	-0.056 (-0.299)	0.061 (0.149)	-0.328 (-0.797)	-1.020 (-1.598)	-0.528 (-0.814)	0.315 (0.285)	-0.485 (-0.427)	0.957 (0.582)	0.064 (0.039)	2.084 (0.857)	1.192 (0.494)
<i>PC4</i>	0.163 (0.988)	0.199 (1.308)	0.611 (1.803)	0.690 (2.138)	1.683 (2.919)	1.184 (2.324)	1.674 (1.924)	1.836 (2.115)	1.779 (1.556)	1.960 (1.718)	1.316 (0.848)	1.497 (0.935)
<i>PC5</i>	-0.328 (-2.235)	-0.368 (-2.799)	-0.670 (-1.875)	-0.756 (-2.157)	2.743 (4.257)	-1.246 (-2.197)	-2.292 (-2.524)	-2.470 (-2.670)	-3.240 (-2.668)	-3.439 (-2.821)	-3.727 (-2.389)	-3.925 (-2.515)
<i>EPU</i>		0.537 (3.899)		1.172 (3.218)		1.697 (2.675)		2.408 (2.245)		2.685 (1.988)		2.681 (1.465)
<i>R</i> ²	0.064	0.087	0.041	0.060	0.038	0.053	0.038	0.048	0.035	0.041	0.026	0.028
<i>3-month holding period</i>												
<i>PC1</i>	0.489 (3.357)	0.618 (4.714)	0.842 (2.393)	1.075 (3.317)	1.115 (1.962)	1.394 (2.647)	1.562 (1.908)	1.869 (2.391)	1.942 (1.692)	2.212 (1.953)	2.493 (1.477)	2.615 (1.533)
<i>PC2</i>	-0.293 (-2.008)	-0.200 (-1.372)	-0.802 (-2.171)	-0.634 (-1.690)	-1.344 (-2.366)	-1.143 (-1.994)	-2.435 (-2.747)	-2.213 (-2.452)	-3.451 (-2.994)	-3.256 (-2.762)	-4.761 (-3.072)	-4.673 (-2.981)
<i>PC3</i>	0.015 (0.106)	-0.106 (-0.728)	-0.198 (-0.574)	-0.416 (-1.133)	-0.448 (-0.840)	-0.710 (-1.217)	-0.711 (-0.818)	-0.999 (-1.150)	-0.611 (-0.540)	-0.865 (-0.776)	-0.171 (-0.116)	-0.286 (-0.203)
<i>PC4</i>	0.224 (1.351)	0.249 (1.534)	0.616 (1.710)	0.661 (1.839)	0.944 (1.787)	0.997 (1.897)	1.320 (1.635)	1.379 (1.765)	1.322 (1.315)	1.374 (1.375)	0.850 (0.620)	0.874 (0.636)
<i>PC5</i>	-0.170 (-1.552)	-0.198 (-2.080)	-0.402 (-1.386)	-0.451 (-1.690)	-0.715 (-1.522)	-0.774 (-1.728)	-1.444 (-1.858)	-1.510 (-1.966)	-2.021 (-2.124)	-2.078 (-2.186)	-2.318 (-1.975)	-2.344 (-1.973)
<i>EPU</i>		0.362 (3.660)		0.652 (2.316)		0.783 (1.651)		0.860 (1.107)		0.758 (0.761)		0.343 (0.272)
<i>R</i> ²	0.154	0.189	0.111	0.127	0.103	0.111	0.100	0.102	0.094	0.094	0.081	0.079
<i>6-month holding period</i>												
<i>PC1</i>	0.301 (2.564)	0.358 (3.349)	0.625 (1.848)	0.754 (2.267)	0.846 (1.155)	0.991 (1.791)	1.203 (1.222)	1.294 (1.315)	1.520 (1.096)	1.493 (1.070)	2.003 (0.996)	1.728 (0.852)
<i>PC2</i>	-0.150 (-1.167)	-0.106 (-0.881)	-0.580 (-1.398)	-0.481 (-1.175)	-1.090 (-1.972)	-0.979 (-1.429)	-2.175 (-1.858)	-2.105 (-1.814)	-3.225 (-2.116)	-3.246 (-2.137)	-4.622 (-2.404)	-4.834 (-2.490)
<i>PC3</i>	0.007 (0.065)	-0.053 (-0.465)	-0.167 (-0.442)	-0.302 (-0.768)	-0.423 (-0.630)	-0.574 (-0.903)	-0.810 (-0.863)	-0.906 (-0.908)	-0.941 (-0.813)	-0.913 (-0.747)	-0.898 (-0.659)	-0.611 (-0.426)
<i>PC4</i>	0.177 (1.526)	0.190 (1.753)	0.605 (1.789)	0.634 (1.948)	0.927 (1.496)	0.960 (1.979)	1.306 (1.843)	1.327 (1.874)	1.385 (1.581)	1.379 (1.558)	1.127 (0.996)	1.066 (0.919)
<i>PC5</i>	-0.057 (-0.875)	-0.073 (-1.207)	-0.190 (-0.807)	-0.225 (-0.993)	-0.405 (-0.929)	-0.444 (-1.146)	-0.917 (-1.391)	-0.941 (-1.447)	-1.353 (-1.582)	-1.346 (-1.573)	-1.674 (-1.521)	-1.600 (-1.450)
<i>EPU</i>		0.169 (2.600)		0.380 (1.567)		0.425 (1.031)		0.268 (0.400)		-0.080 (-0.092)		-0.809 (-0.724)
<i>R</i> ²	0.217	0.245	0.170	0.183	0.165	0.170	0.171	0.169	0.170	0.168	0.159	0.159
<i>12-month holding period</i>												
<i>PC1</i>			0.377 (1.580)	0.468 (2.079)	0.567 (1.899)	0.712 (1.675)	1.001 (0.983)	1.096 (1.037)	1.036 (0.963)	1.116 (0.999)	1.378 (0.828)	1.306 (0.771)
<i>PC2</i>			-0.213 (-0.682)	-0.138 (-0.451)	-0.561 (-1.183)	-0.442 (-0.784)	-2.287 (-1.961)	-2.210 (-1.891)	-2.454 (-2.036)	-2.388 (-1.981)	-3.887 (-2.656)	-3.945 (-2.597)
<i>PC3</i>			0.016 (0.066)	-0.090 (-0.451)	-0.044 (-0.117)	-0.212 (-0.529)	-0.202 (-0.236)	-0.312 (-0.364)	-0.206 (-0.235)	-0.299 (-0.339)	-0.226 (-0.221)	-0.143 (-0.131)
<i>PC4</i>			0.384 (2.077)	0.410 (2.439)	0.683 (2.346)	0.724 (2.604)	1.049 (1.979)	1.076 (2.044)	1.037 (1.897)	1.060 (1.946)	0.744 (1.011)	0.724 (0.995)
<i>PC5</i>			-0.104 (-0.643)	-0.134 (-0.898)	-0.250 (-0.894)	-0.297 (-1.095)	-0.851 (-1.645)	-0.881 (-1.706)	-0.894 (-1.698)	-0.919 (-1.734)	-1.132 (-1.801)	-1.109 (-1.745)
<i>EPU</i>				0.281 (2.321)		0.446 (1.871)		0.292 (0.572)		0.247 (0.466)		-0.220 (-0.306)
<i>R</i> ²			0.196	0.226	0.179	0.198	0.216	0.215	0.219	0.218	0.238	0.236

Notes: This table reports the coefficient estimates in a regression of the annualised bond excess returns on six n -month maturity bond ranging 12 to 120-month, with a holding period of 1 month. *EPU* is economic policy uncertainty index of Baker et al. (2016). *PCs* are the first five principal components of Treasury yields. All the dependant variables in the regression are standardised to have a mean of 0 and a standard deviation of 1. The values in parentheses are the Newey and West (1987) t-statistics with the optimal length determined based on Newey and West (1994). The sample period covers from 1985:01 to 2015:12.

Table 3.5: *EPU* Return Predictability with Additional Factors (1-month holding period)

	1y			2y			3y			5y			7y			10y		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
<i>PC1</i>	0.558 (3.510)	0.565 (2.694)	0.792 (4.628)	0.789 (2.136)	0.729 (1.491)	1.325 (3.455)	0.887 (1.434)	0.781 (0.997)	1.743 (3.263)	0.874 (0.788)	0.687 (0.501)	2.359 (2.459)	0.784 (0.505)	0.430 (0.226)	2.754 (2.037)	0.859 (0.423)	0.036 (0.013)	3.215 (1.537)
<i>PC2</i>	0.213 (1.155)	0.043 (0.215)	-0.203 (-1.241)	0.386 (0.823)	0.085 (0.174)	-0.593 (-1.496)	0.571 (0.752)	0.089 (0.115)	-1.031 (-1.831)	0.899 (0.721)	0.028 (0.022)	-1.980 (-2.266)	0.986 (0.602)	-0.071 (-0.041)	-2.935 (-2.723)	0.585 (0.288)	-0.203 (-0.086)	-4.224 (-2.894)
<i>PC3</i>	-0.186 (-1.090)	0.062 (0.332)	-0.117 (-0.684)	-0.630 (-1.585)	-0.008 (-0.018)	-0.439 (-1.148)	-1.020 (-1.598)	0.003 (0.005)	-0.664 (-1.090)	-1.369 (-1.245)	0.465 (0.375)	-0.606 (-0.555)	-1.156 (-0.754)	1.392 (0.780)	0.017 (0.010)	-0.347 (-0.160)	2.969 (1.160)	1.274 (0.516)
<i>EPU</i>	0.539 (3.966)	0.539 (3.681)	0.370 (2.486)	1.167 (3.414)	1.193 (2.998)	0.802 (2.026)	1.683 (2.919)	1.727 (2.551)	1.136 (1.695)	2.384 (2.399)	2.464 (2.154)	1.575 (1.370)	2.697 (2.051)	2.837 (1.844)	1.787 (1.148)	2.813 (1.650)	3.108 (1.386)	1.993 (1.013)
<i>CP</i>	0.712 (4.786)			1.676 (4.447)			2.743 (4.257)			4.925 (4.094)			6.705 (3.800)			8.210 (3.375)		
<i>Cycle</i>	0.467 (1.982)				1.290 (2.153)			2.130 (2.212)			3.815 (2.315)			5.437 (2.438)			7.619 (2.352)	
<i>MacroU</i>			0.308 (1.539)			0.600 (1.111)			0.821 (1.036)			1.036 (0.804)			0.966 (0.563)			0.631 (0.291)
<i>FinU</i>			0.147 (0.749)			0.314 (0.606)			0.454 (0.575)			0.565 (0.439)			0.474 (0.283)			0.075 (0.034)
<i>R</i> ²	0.103	0.078	0.081	0.075	0.053	0.048	0.067	0.045	0.036	0.063	0.039	0.024	0.059	0.036	0.018	0.047	0.034	0.014

Notes: This table reports the coefficient estimates in a regression of the annualised bond excess returns on six n -month maturity bond ranging 12 to 120-month, with a holding period of 1 month. *PCs* are the first three principal components of Treasury yields representing the level, slope, and curvature of yield curve. *EPU* is economic policy uncertainty index of Baker et al. (2016). *CP* and *Cycle* are the return forecasting factors from Cochrane and Piazzesi (2005) and Cieslak and Povala (2014), respectively. *MacroU* is the macroeconomic uncertainty of Jurado et al. (2015) and *FinU* is the financial uncertainty measure introduced by Ludvigson et al. (2017). All the dependant variables in the regression are standardised to have mean 0 and a standard deviation of 1. The values in parentheses are the Newey and West (1987) t -statistics with the optimal length determined based on Newey and West (1994). The sample period covers from 1985:01 to 2015:12.

Table 3.6: *EPU* Return Predictability with Additional Factors (3-month holding period)

	1y			2y			3y			5y			7y			10y		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
<i>PC1</i>	0.398 (2.861)	0.453 (2.151)	0.643 (5.330)	0.489 (1.329)	0.613 (1.123)	1.124 (3.764)	0.449 (0.727)	0.652 (0.737)	1.457 (3.015)	0.245 (0.244)	0.588 (0.457)	1.939 (2.273)	0.085 (0.063)	0.439 (0.243)	2.275 (1.833)	0.214 (0.113)	0.252 (0.099)	2.667 (1.447)
<i>PC2</i>	0.176 (0.891)	-0.011 (-0.044)	-0.219 (-1.436)	0.376 (0.722)	-0.095 (-0.153)	-0.678 (-1.746)	0.489 (0.617)	-0.275 (-0.285)	-1.210 (-2.070)	0.602 (0.479)	-0.705 (-0.501)	-2.319 (-2.523)	0.457 (0.276)	-1.135 (-0.600)	-3.381 (-2.795)	-0.433 (-0.194)	-1.763 (-0.702)	-4.795 (-2.946)
<i>PC3</i>	-0.046 (-0.322)	-0.001 (-0.008)	-0.158 (-1.115)	-0.258 (-0.743)	-0.127 (-0.329)	-0.532 (-1.760)	-0.456 (-0.912)	-0.247 (-0.418)	-0.873 (-1.845)	-0.566 (-0.711)	-0.201 (-0.234)	-1.191 (-1.539)	-0.311 (-0.298)	0.220 (0.200)	-1.024 (-1.001)	0.311 (0.228)	1.108 (0.789)	-0.351 (-0.258)
<i>EPU</i>	0.350 (3.924)	0.367 (3.449)	0.234 (1.947)	0.629 (2.554)	0.681 (2.184)	0.333 (0.969)	0.748 (1.741)	0.831 (1.542)	0.287 (0.507)	0.814 (1.142)	0.960 (0.984)	0.126 (0.131)	0.730 (0.786)	0.953 (0.728)	-0.024 (-0.019)	0.379 (0.317)	0.750 (0.451)	-0.243 (-0.153)
<i>CP</i>	0.551 (3.525)			1.475 (3.467)			2.382 (3.534)			4.105 (3.760)			5.398 (3.635)			6.135 (2.914)		
<i>Cycle</i>	0.386 (1.327)			1.091 (1.488)			1.757 (1.538)			3.044 (1.826)			4.246 (1.848)				5.738 (1.869)	
<i>MacroU</i>			0.319 (1.599)			0.703 (1.470)			1.003 (1.351)			1.338 (1.158)			1.356 (0.916)			1.077 (0.552)
<i>FinU</i>			0.084 (0.416)			0.244 (0.506)			0.400 (0.524)			0.577 (0.474)			0.543 (0.343)			0.216 (0.104)
<i>R²</i>	0.194	0.173	0.186	0.138	0.118	0.120	0.124	0.104	0.100	0.121	0.100	0.085	0.117	0.100	0.074	0.100	0.098	0.065

Notes: This table reports the coefficient estimates in a regression of the annualised bond excess returns on six n -month maturity bond ranging 12 to 120-month, with a holding period of 3 months. *PCs* are the first three principal components of Treasury yields representing the level, slope, and curvature of yield curve. *EPU* is economic policy uncertainty index of Baker et al. (2016). *CP* and *Cycle* are the return forecasting factors from Cochrane and Piazzesi (2005) and Cieslak and Povala (2014), respectively. *MacroU* is the macroeconomic uncertainty of Jurado et al. (2015) and *FinU* is the financial uncertainty measure introduced by Ludvigson et al. (2017). All the dependant variables in the regression are standardised to have mean 0 and a standard deviation of 1. The values in parentheses are the Newey and West (1987) t-statistics with the optimal length determined based on Newey and West (1994). The sample period covers from 1985:01 to 2015:12.

Table 3.7: *EPU* Return Predictability with Additional Factors (1-month holding period)

	1y	2y	3y	5y	7y	10y
<i>PC1</i>	0.461 (2.155)	0.432 (0.738)	0.227 (0.239)	-0.505 (-0.305)	-1.406 (-0.568)	-2.508 (-0.830)
<i>PC2</i>	0.337 (1.407)	0.832 (1.306)	1.385 (1.364)	2.580 (1.517)	3.649 (1.522)	4.709 (1.565)
<i>PC3</i>	-0.141 (-0.819)	-0.445 (-1.168)	-0.666 (-1.132)	-0.598 (-0.588)	0.106 (0.071)	1.654 (0.754)
<i>EPU</i>	0.510 (3.266)	1.184 (2.824)	1.786 (2.449)	2.803 (2.238)	3.580 (2.094)	4.488 (1.975)
<i>CP</i>	0.626 (4.257)	1.515 (3.860)	2.549 (3.804)	4.782 (3.737)	6.717 (3.442)	8.485 (2.954)
<i>Cycle</i>	0.329 (1.385)	1.020 (1.723)	1.750 (1.847)	3.335 (2.019)	5.026 (2.222)	7.526 (2.603)
<i>MacroU</i>	0.122 (0.639)	0.148 (0.281)	0.060 (0.070)	-0.392 (-0.277)	-1.046 (-0.531)	-1.925 (-0.813)
<i>FinU</i>	0.110 (0.542)	0.188 (0.365)	0.237 (0.292)	0.151 (0.114)	-0.162 (-0.095)	-0.913 (-0.419)
<i>R</i> ²	0.107	0.079	0.071	0.069	0.066	0.057

Notes: This table reports the coefficient estimates in a regression of the annualised bond excess returns on six n -month maturity bond ranging 12 to 120-month, with a holding period of 1 month. *PCs* are the first three principal components of Treasury yields representing the level, slope, and curvature of yield curve. *EPU* is economic policy uncertainty index of Baker et al. (2016). *CP* and *Cycle* are the return forecastig factors from Cochrane and Piazzesi (2005) and Cieslak and Povala (2014), respectively. *MacroU* is the macroeconomic uncertainty of Jurado et al. (2015) and *FinU* is the financial uncertainty measure introduced by Ludvigson et al. (2017). All the dependant variables in the regression are standardised to have mean 0 and a standard deviation of 1. The values in parentheses are the Newey and West (1987) t-statistics with the optimal length determined based on Newey and West (1994). The sample period covers from 1985:01 to 2015:12.

Table 3.8: *EPU* Return Predictability with Additional Factors (3-month holding period)

	1y	2y	3y	5y	7y	10y
<i>PC1</i>	0.430 (1.957)	0.560 (1.253)	0.547 (0.731)	0.302 (0.186)	-0.088 (-0.039)	-0.564 (-0.177)
<i>PC2</i>	0.125 (0.431)	0.213 (0.366)	0.220 (0.232)	0.231 (0.129)	0.257 (0.107)	0.075 (0.023)
<i>PC3</i>	-0.145 (-0.998)	-0.453 (-1.355)	-0.737 (-1.427)	-0.925 (-1.192)	-0.586 (-0.603)	0.420 (0.326)
<i>EPU</i>	0.328 (2.462)	0.588 (1.663)	0.700 (1.164)	0.873 (0.750)	1.060 (0.697)	1.255 (0.663)
<i>CP</i>	0.325 (1.924)	0.740 (1.868)	1.162 (1.748)	2.021 (1.896)	2.757 (1.880)	3.277 (1.528)
<i>Cycle</i>	0.282 (0.995)	0.852 (1.355)	1.399 (1.411)	2.570 (1.539)	3.825 (1.715)	5.607 (1.911)
<i>MacroU</i>	0.202 (1.102)	0.444 (0.903)	0.610 (0.776)	0.699 (0.563)	0.521 (0.313)	0.115 (0.050)
<i>FinU</i>	0.052 (0.260)	0.133 (0.284)	0.210 (0.290)	0.207 (0.163)	-0.026 (-0.016)	-0.642 (-0.302)
<i>R</i> ²	0.217	0.151	0.132	0.121	0.116	0.106

Notes: This table reports the coefficient estimates in a regression of the annualised bond excess returns on six n -month maturity bond ranging 12 to 120-month, with a holding period of 3 months. *PCs* are the first three principal components of Treasury yields representing the level, slope, and curvature of yield curve. *EPU* is economic policy uncertainty index of Baker et al. (2016). *CP* and *Cycle* are the return forecasting factors from Cochrane and Piazzesi (2005) and Cieslak and Povala (2014), respectively. *MacroU* is the macroeconomic uncertainty of Jurado et al. (2015) and *FinU* is the financial uncertainty measure introduced by Ludvigson et al. (2017). All the dependant variables in the regression are standardised to have mean 0 and a standard deviation of 1. The values in parentheses are the Newey and West (1987) t -statistics with the optimal length determined based on Newey and West (1994). The sample period covers from 1985:01 to 2015:12.

Table 3.9: J-test for Model Specification

	1y	2y	3y	5y	7y	10y
Panel A. Test for M1						
<i>PC1</i>	0.453 (1.432)	0.547 (0.729)	0.411 (0.339)	-0.188 (-0.092)	-0.228 (-0.085)	1.296 (0.371)
<i>PC2</i>	0.243 (1.063)	0.456 (0.798)	0.710 (0.781)	1.209 (0.826)	1.282 (0.678)	0.457 (0.192)
<i>PC3</i>	-0.201 (-1.102)	-0.666 (-1.555)	-1.089 (-1.588)	-1.524 (-1.322)	-1.303 (-0.837)	-0.283 (-0.130)
<i>CP</i>	0.634 (3.200)	1.496 (3.171)	2.391 (2.995)	4.139 (2.612)	5.957 (2.417)	8.533 (2.332)
<i>EPU</i>	0.543 (3.956)	1.178 (3.458)	1.704 (2.960)	2.432 (2.422)	2.743 (2.077)	2.793 (1.500)
\widehat{rx}_{M1}	0.224 (0.427)	0.517 (0.442)	1.016 (0.537)	2.268 (0.671)	2.159 (0.448)	-0.933 (-0.142)
R^2	0.101	0.072	0.065	0.062	0.056	0.045
Panel A. Test for M2						
<i>PC1</i>	0.023 (0.129)	-0.369 (-0.754)	-0.765 (-0.995)	-1.416 (-1.056)	-1.887 (-0.972)	-2.289 (-0.834)
<i>PC2</i>	-0.013 (-0.090)	-0.156 (-0.400)	-0.348 (-0.568)	-0.840 (-0.824)	-1.380 (-1.000)	-2.156 (-1.201)
<i>PC3</i>	0.004 (0.026)	-0.203 (-0.543)	-0.361 (-0.614)	-0.304 (-0.300)	0.167 (0.116)	1.104 (0.533)
<i>PC4</i>	0.020 (0.130)	0.290 (0.870)	0.585 (1.155)	0.920 (1.102)	0.818 (0.719)	0.124 (0.080)
<i>PC5</i>	-0.050 (-0.360)	-0.046 (-0.125)	-0.181 (-0.305)	-0.829 (-0.844)	-1.374 (-1.059)	-1.412 (-0.833)
\widehat{rx}_{M2}	0.961 (5.780)	2.149 (3.945)	3.238 (3.559)	5.042 (3.070)	6.432 (2.691)	7.978 (2.409)
R^2	0.101	0.074	0.067	0.062	0.055	0.042

Notes: This table reports model specification results based on the J-test proposed by Davidson and Mackinnon (1981, 1993). We compare two non-nested models described as

$$\begin{aligned}
 M1: rx_{t+1}^{(n)} &= \gamma_0^{(n)} + \gamma_1^{(n)} PC_t^{1,\dots,5} + \varepsilon_{t+1}^{(n)} \quad \text{and} \\
 M2: rx_{t+1}^{(n)} &= \beta_0^{(n)} + \beta_1^{(n)} PC_t^{1,2,3} + \beta_2^{(n)} CP_t + \beta_3^{(n)} EPU_t + \eta_{t+1}^{(n)},
 \end{aligned}$$

where model 1 (*M1*) uses the first five *PCs* of interest rates, whilst model 2 (*M2*) has the first three *PCs*, *CP*, and *EPU* as bond return forecasting factors. *CP* is the return forecasting factor from Cochrane and Piazzesi (2005) and *EPU* is economic policy uncertainty index of Baker et al. (2016). J-test adds the fitted value from one model ($\widehat{rx}_{M1,t+1}^{(n)}$ and $\widehat{rx}_{M2,t+1}^{(n)}$) into the other one and examines the significance of the additional regressor using the *t*-test. All the dependant variables in the initial regressions are standardised to have mean 0 and a standard deviation of 1. The values in parentheses are the Newey and West (1987) *t*-statistics with the optimal length determined based on Newey and West (1994). The sample period covers from 1985:01 to 2015:12.

Table 3.10: Yield-Plus Model: Pricing Errors

	12m	24m	36m	60m	84m	120m
<i>Panel A. Yield Pricing Error</i>						
	12m	24m	36m	60m	84m	120m
Mean	0.092	0.111	0.080	-0.020	-0.069	-0.005
Std. Dev.	0.121	0.091	0.040	0.084	0.096	0.067
Skewness	0.261	1.191	0.781	-0.471	-0.496	0.284
Kurtosis	6.124	6.065	5.235	4.572	3.581	5.729
AC(1)	0.826	0.945	0.780	0.938	0.980	0.806
AC(6)	0.669	0.801	0.589	0.817	0.908	0.570
<i>Panel B. Return Pricing Error</i>						
	12m	24m	36m	60m	84m	120m
Mean	0.006	0.009	-0.005	-0.020	-0.011	0.040
Std. Dev.	0.094	0.081	0.095	0.158	0.143	0.416
Skewness	0.245	0.892	-0.576	-0.854	-1.090	0.864
Kurtosis	8.632	11.820	7.930	10.161	17.955	9.931
AC(1)	-0.067	-0.096	-0.169	0.023	0.188	-0.187
AC(6)	0.144	0.003	0.112	0.046	-0.003	0.035

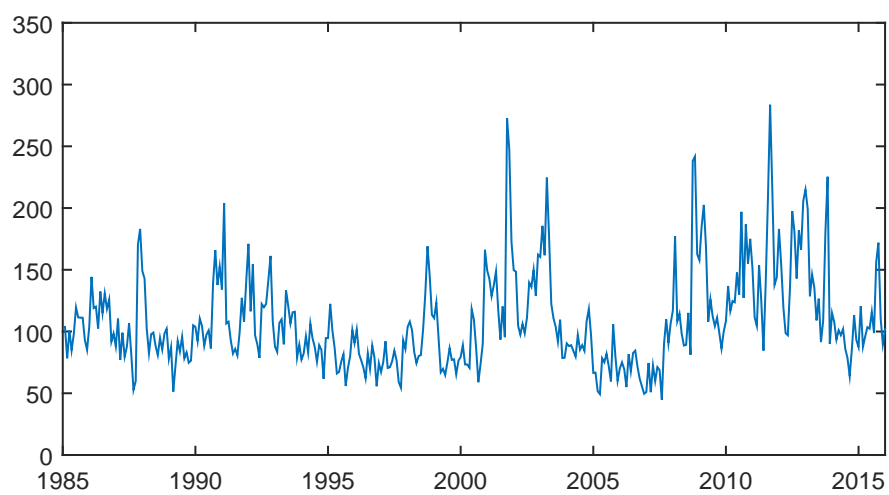
Notes: This table reports the pricing errors from the term structure estimation following yield-plus approach. The pricing factors include the first three principal components of Treasury yields, Cochrane and Piazzesi (2005)'s return forecasting factor, and the economic policy uncertainty index by Baker et al. (2016). Panel A shows the yield pricing error $\hat{u}^{(n)}$, whilst Panel B shows the return pricing error $\hat{e}^{(n)}$.

Table 3.11: Yield-Only Model: Pricing Errors

	12m	24m	36m	60m	84m	120m
<i>Panel A. Yield Pricing Error</i>						
Mean	0.110	0.053	0.031	0.016	0.007	-0.002
Std. Dev.	0.094	0.031	0.017	0.007	0.012	0.019
Skewness	0.776	-0.095	-0.040	-0.555	-0.941	-0.279
Kurtosis	4.182	3.282	4.932	3.432	6.775	3.392
AC(1)	0.953	0.967	0.825	0.811	0.793	0.788
AC(6)	0.787	0.877	0.628	0.580	0.591	0.566
<i>Panel B. Return Pricing Error</i>						
Mean	0.002	-0.001	-0.001	-0.001	-0.002	-0.001
Std. Dev.	0.061	0.058	0.064	0.063	0.082	0.133
Skewness	-0.498	-0.733	-0.501	-0.598	-0.545	-0.017
Kurtosis	9.929	9.314	7.689	8.225	10.728	9.476
AC(1)	-0.035	0.086	0.064	0.135	-0.036	-0.144
AC(6)	0.074	0.010	0.002	0.056	0.044	0.028

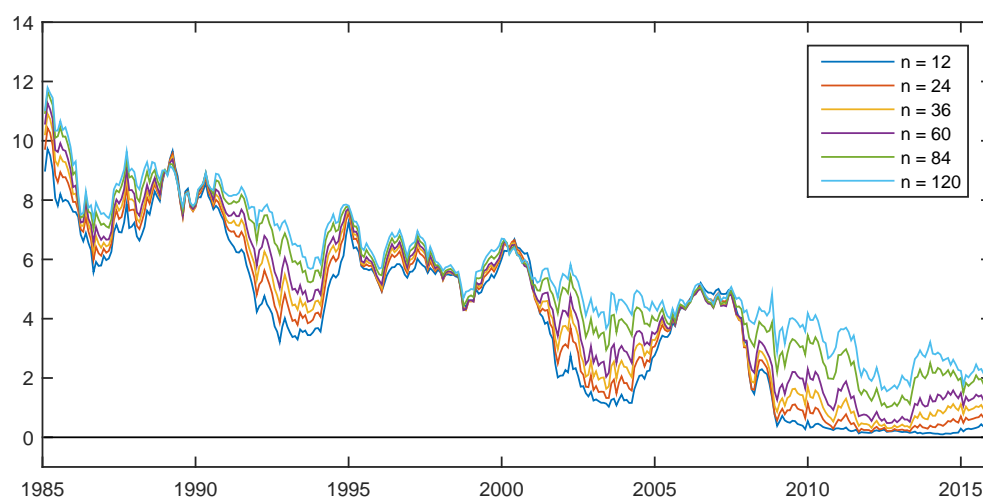
Notes: This table reports the pricing errors from the term structure estimation following yield-plus approach. The pricing factors include the first three principal components of Treasury yields, Cochrane and Piazzesi (2005)'s return forecasting factor, and the economic policy uncertainty index by Baker et al. (2016). Panel A shows the yield pricing error $\hat{u}^{(n)}$, whilst Panel B shows the return pricing error $\hat{e}^{(n)}$.

Figure 3-1: Economic Policy Uncertainty



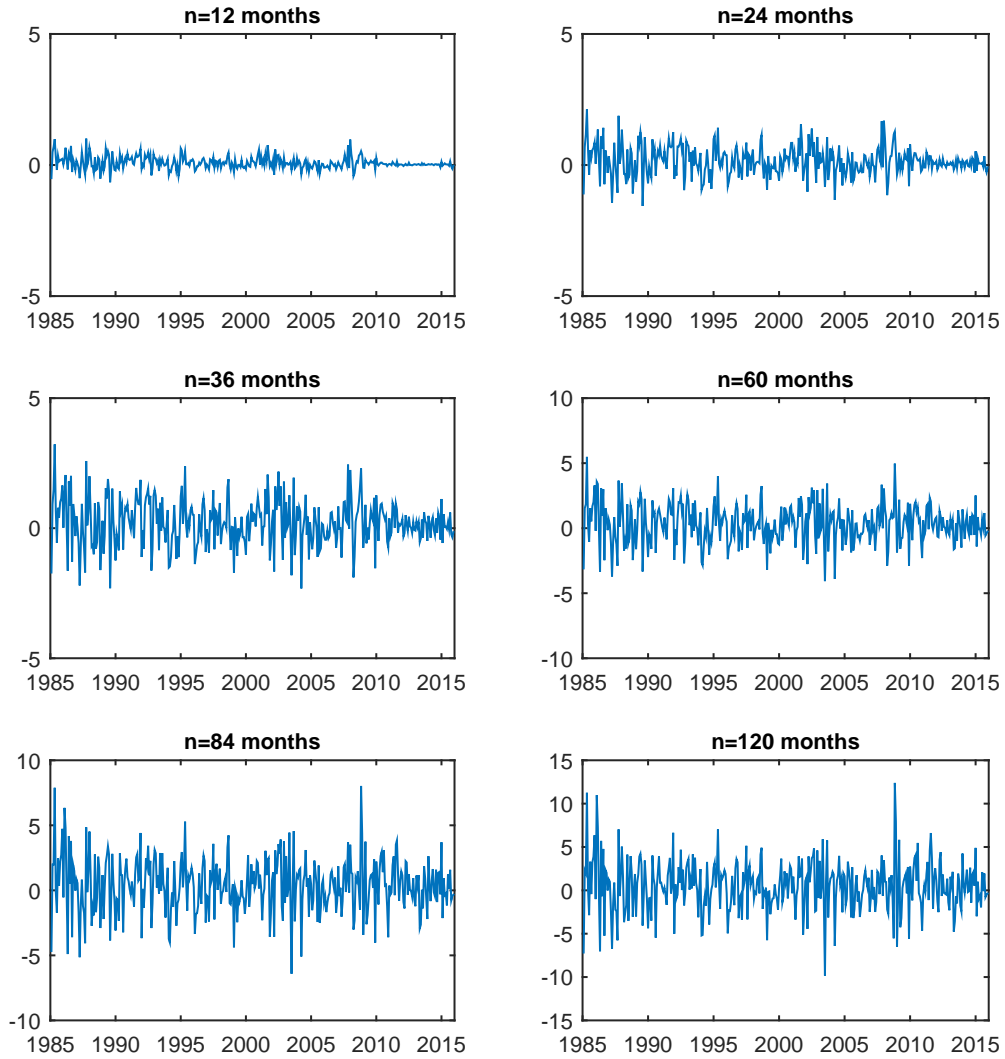
Notes: This figure plots monthly Economic Policy Uncertainty index constructed by Baker et al. (2016). The sample period covers from 1985:01 to 2015:12 and the series is normalised to have a mean of 100.

Figure 3-2: Treasury Bond Yields



Notes: This figure plots time series of Treasury bond yields (in percentage) for selective maturities (n) ranging from 12 months to 120 months. Sample period is from 1985:01 to 2015:12.

Figure 3-3: Treasury Bond Excess Returns (1-month holding period)

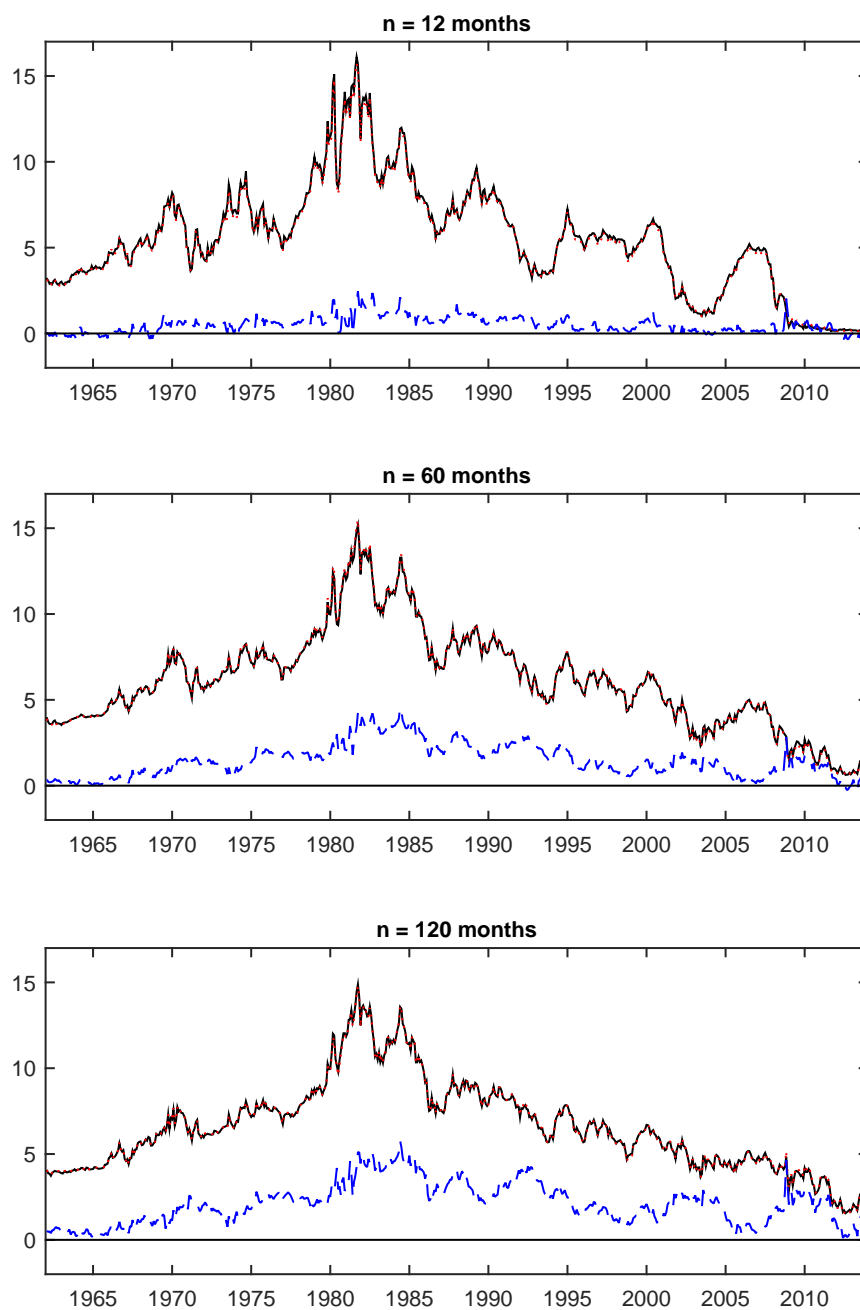


Notes: This figure plots time series of bond monthly bond excess returns (in percentage) for selective maturities (n) ranging from 12 months to 120 months. Monthly bond excess returns are constructed from Treasuries with maturity (n):

$$rx_{t+1}^{(n)} = r_{t+1}^{(n)} - y_t^{(1)},$$

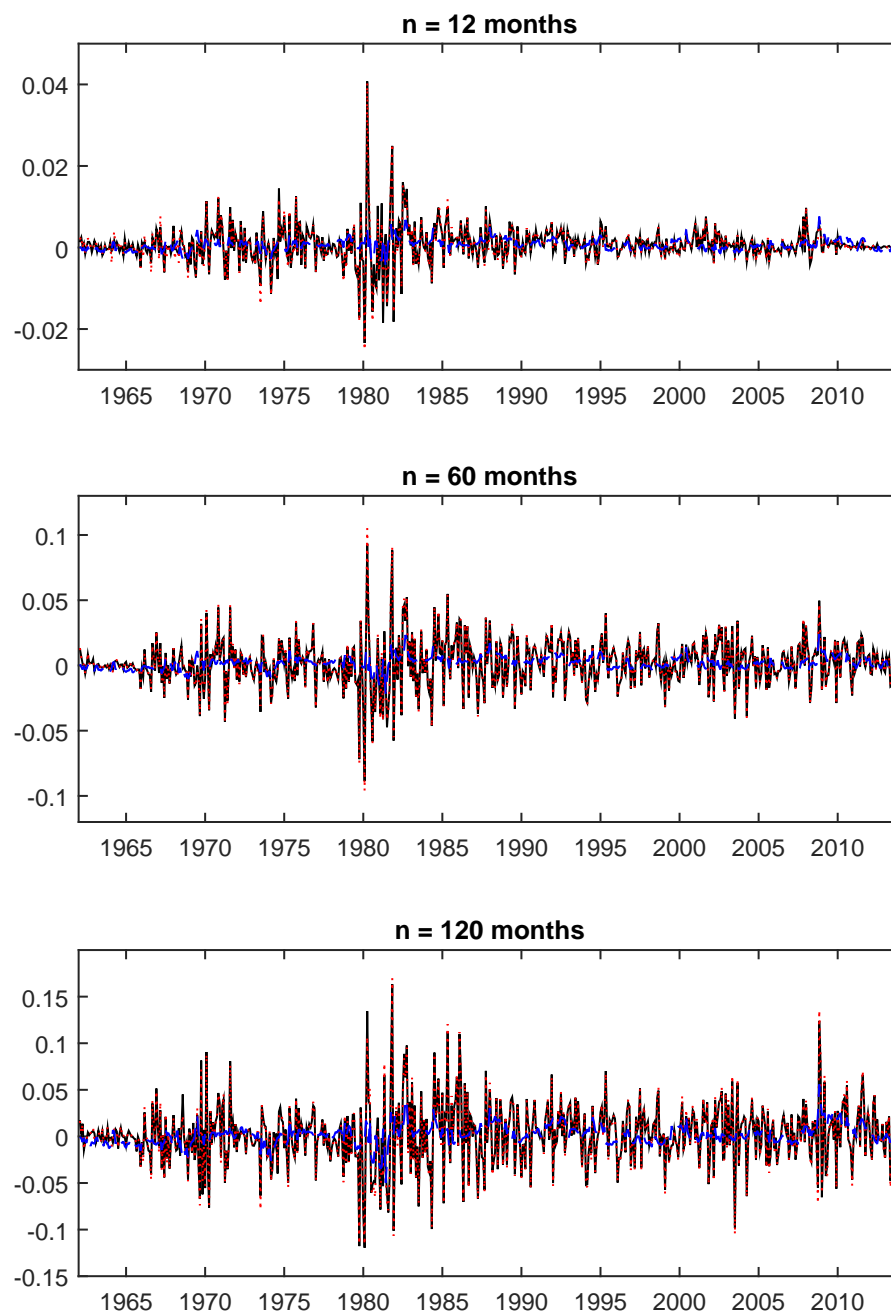
where $r_{t+1}^{(n)}$ is the log return holding n -month bond ($r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}$). Sample period is from 1985:01 to 2015:12.

Figure 3-4: Fitted Yield and Term Premium (Yield-Plus model)



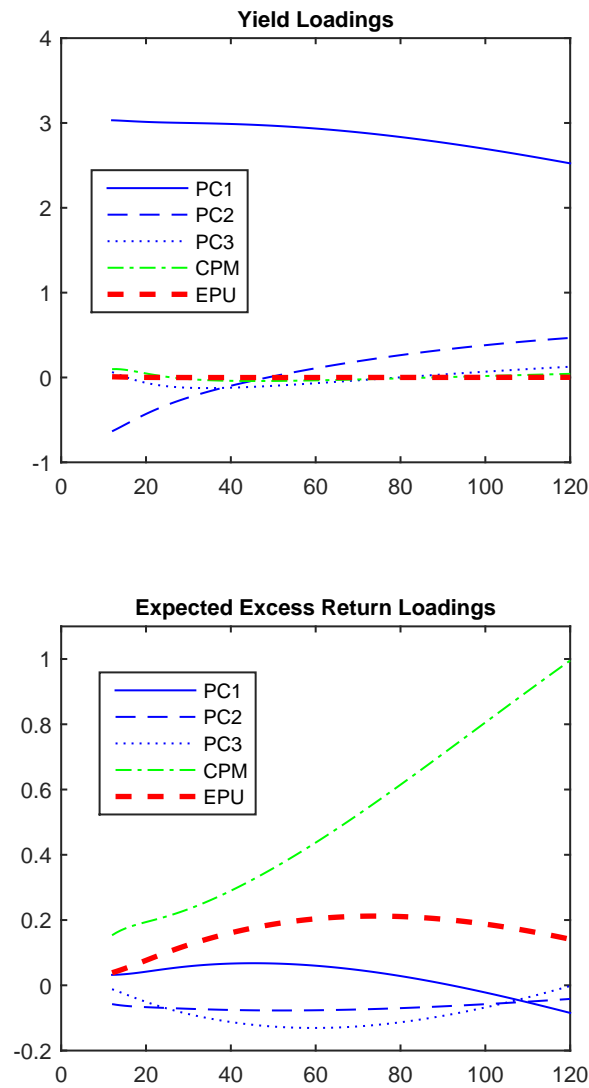
Notes: This figure plots the actual and fitted yields and term premia for 12, 60, and 120 months maturities. The observed yields are plotted with solid line and dotted line show fitted yields. The model implied term premia for corresponding maturities are plotted by dashed lines.

Figure 3-5: Observed and Model-Implied Excess Returns (Yield-Plus model)



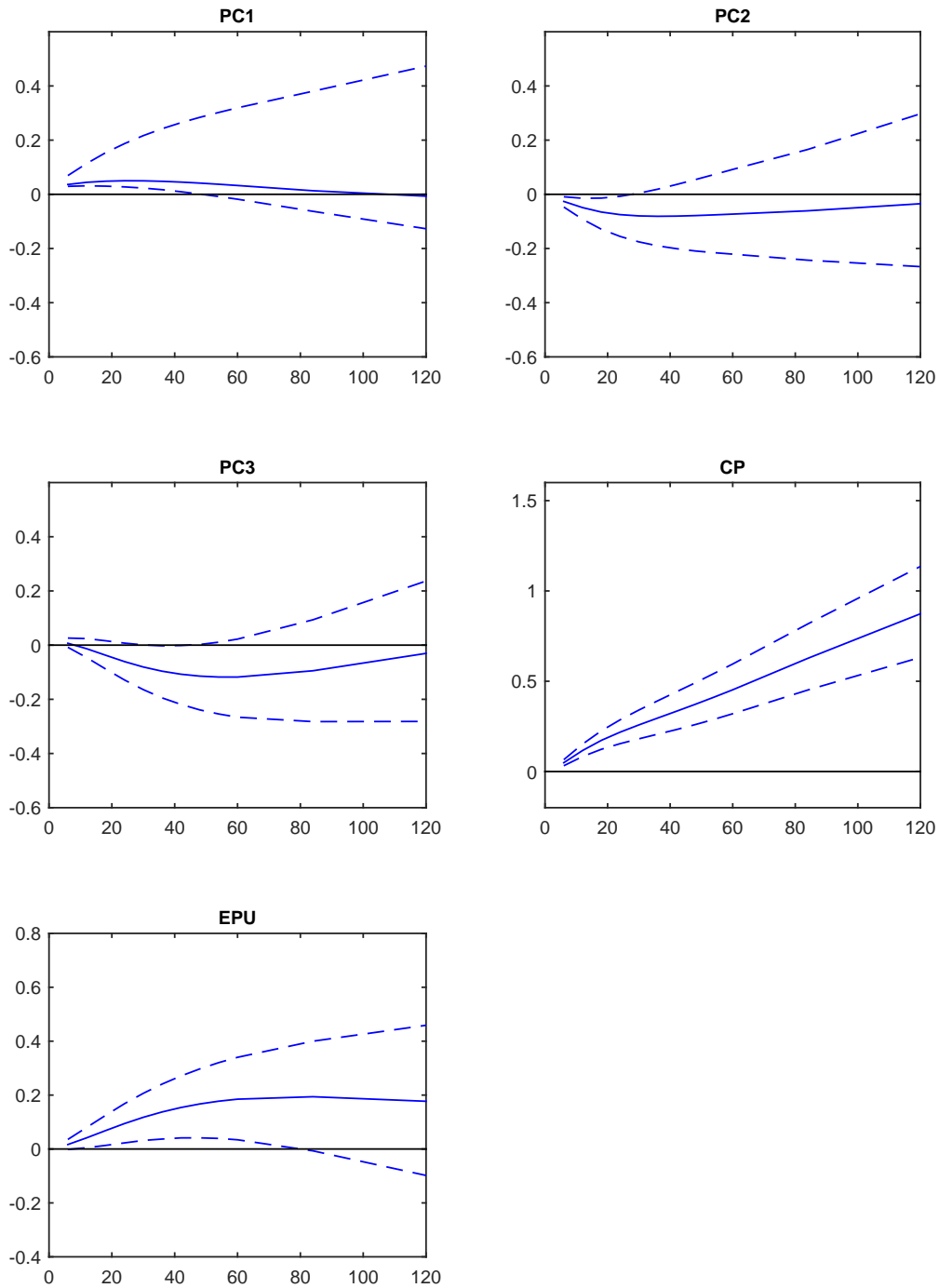
Notes: This figure plots the actual and fitted yields and term premia for 12, 60, and 120 months maturities. The observed yields are plotted with solid line and dotted line show fitted yields. The model implied term premia for corresponding maturities are plotted by dashed lines.

Figure 3-6: Factor Loadings (Yield-Plus model)



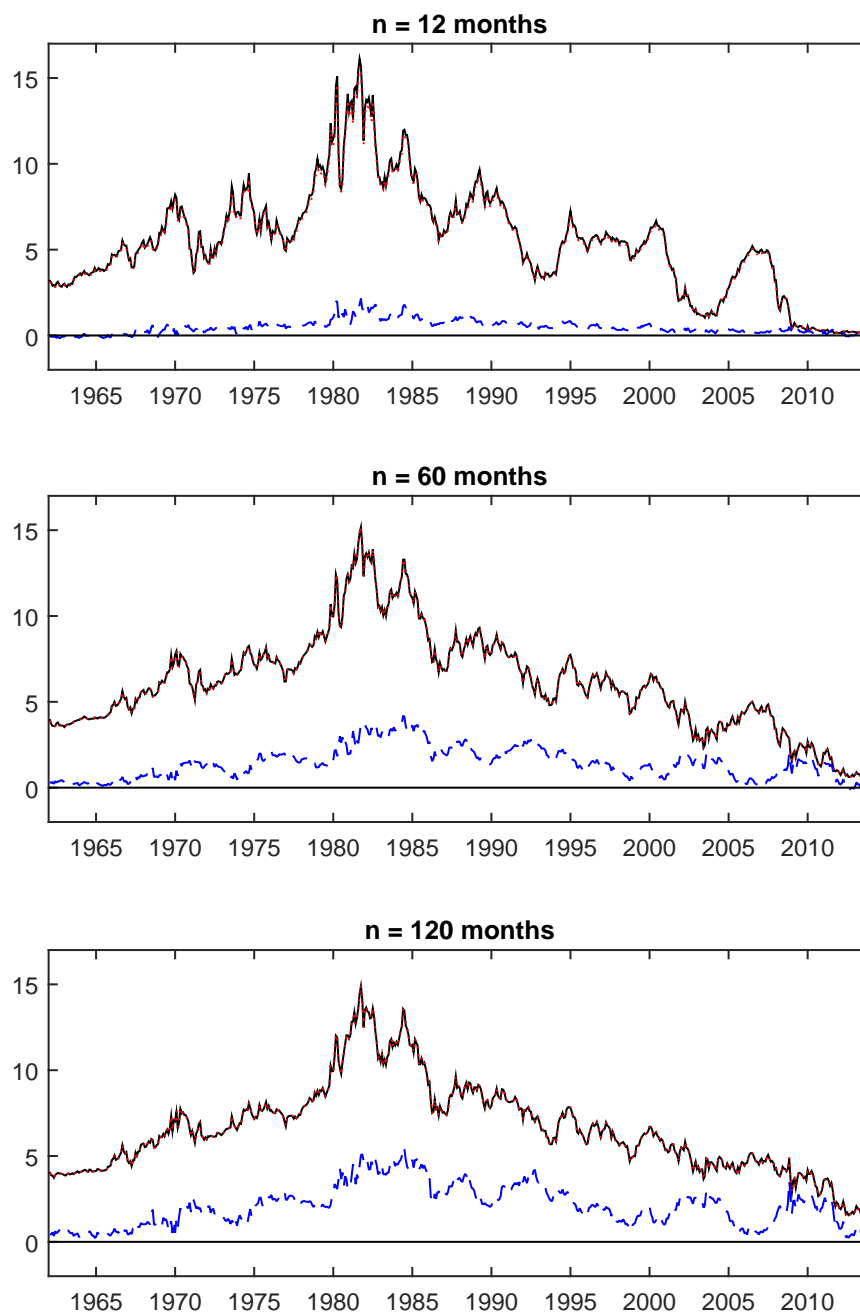
Notes: This figure plots the model implied loadings for yields and excess returns. The upper panel shows the loadings ($b_n = -\frac{1}{n}B_n$) for yields across 12 to 120-month maturities. The lower panel plots the loadings ($B'_n\lambda_1$) for expected one month holding period excess returns for the same maturities. Factors are the first three principal components of Treasury yields, Cochrane and Piazzesi (2005)'s return forecasting factor, and Economic Policy Uncertainty of Baker et al. (2016). Sample period is from 1962:01 to 2013:12.

Figure 3-7: Factor Loadings with Confidence Intervals (Yield-Plus model)



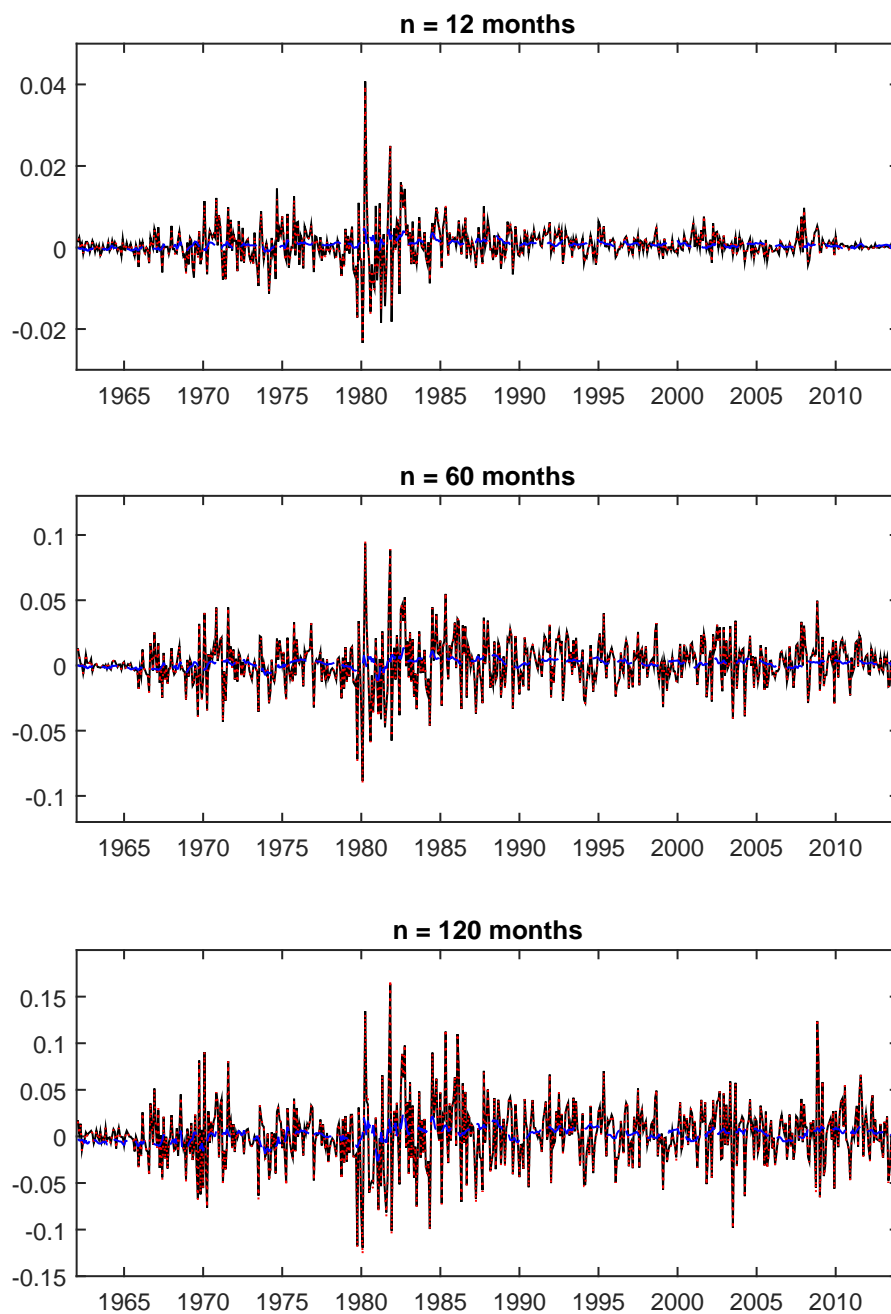
Notes: This figure plots the model implied loadings for excess returns with 90% confidence intervals for the factor loadings. Confidence intervals are calculated using a bootstrap procedure introduced by Malik and Meldrum (2016) with 10,000 replications. Factors are the first three principal components of Treasury yields, Cochrane and Piazzesi (2005)'s return forecasting factor, and Economic Policy Uncertainty of Baker et al. (2016). Sample period is from 1962:01 to 2013:12.

Figure 3-8: Fitted Yield and Term Premium (Yield-Only model)



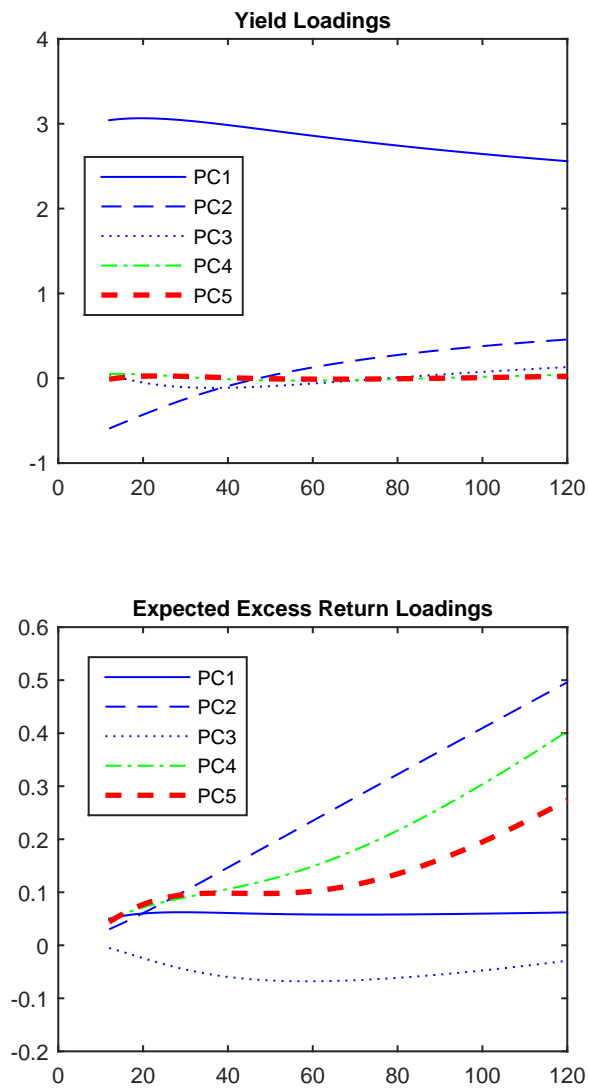
Notes: This figure plots the actual and fitted excess returns for 12, 60, and 120 months maturities. The observed monthly excess returns are plotted with solid line and dotted line show model implied returns. The expected components of excess returns for corresponding maturities are plotted by dashed lines.

Figure 3-9: Observed and model-implied excess returns (Yield-Only model)



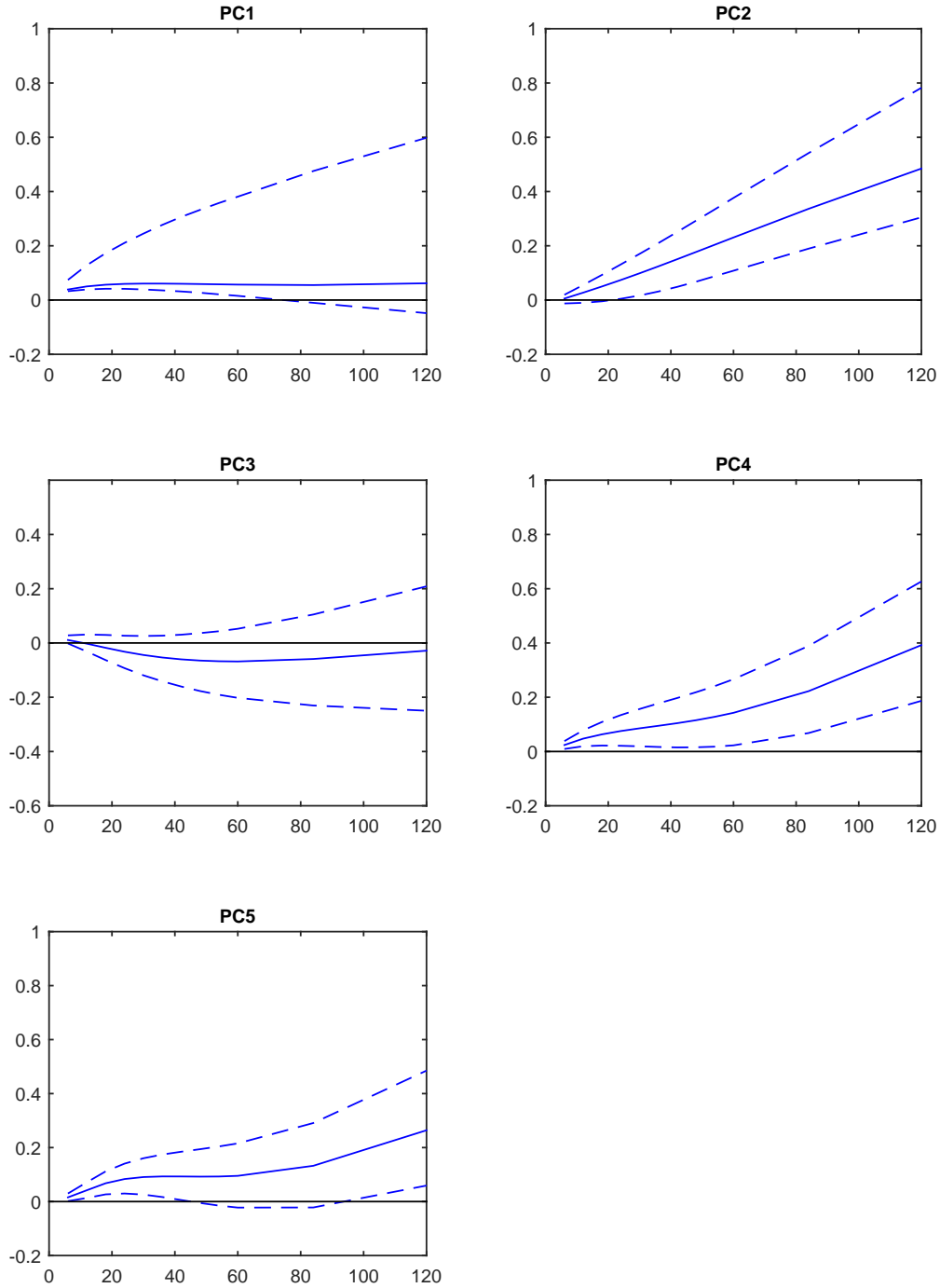
Notes: This figure plots the actual and fitted excess returns for 12, 60, and 120 months maturities. The observed monthly excess returns are plotted with solid line and dotted line show model implied returns. The expected components of excess returns for corresponding maturities are plotted by dashed lines.

Figure 3-10: Factor Loadings (Yield-Only model)



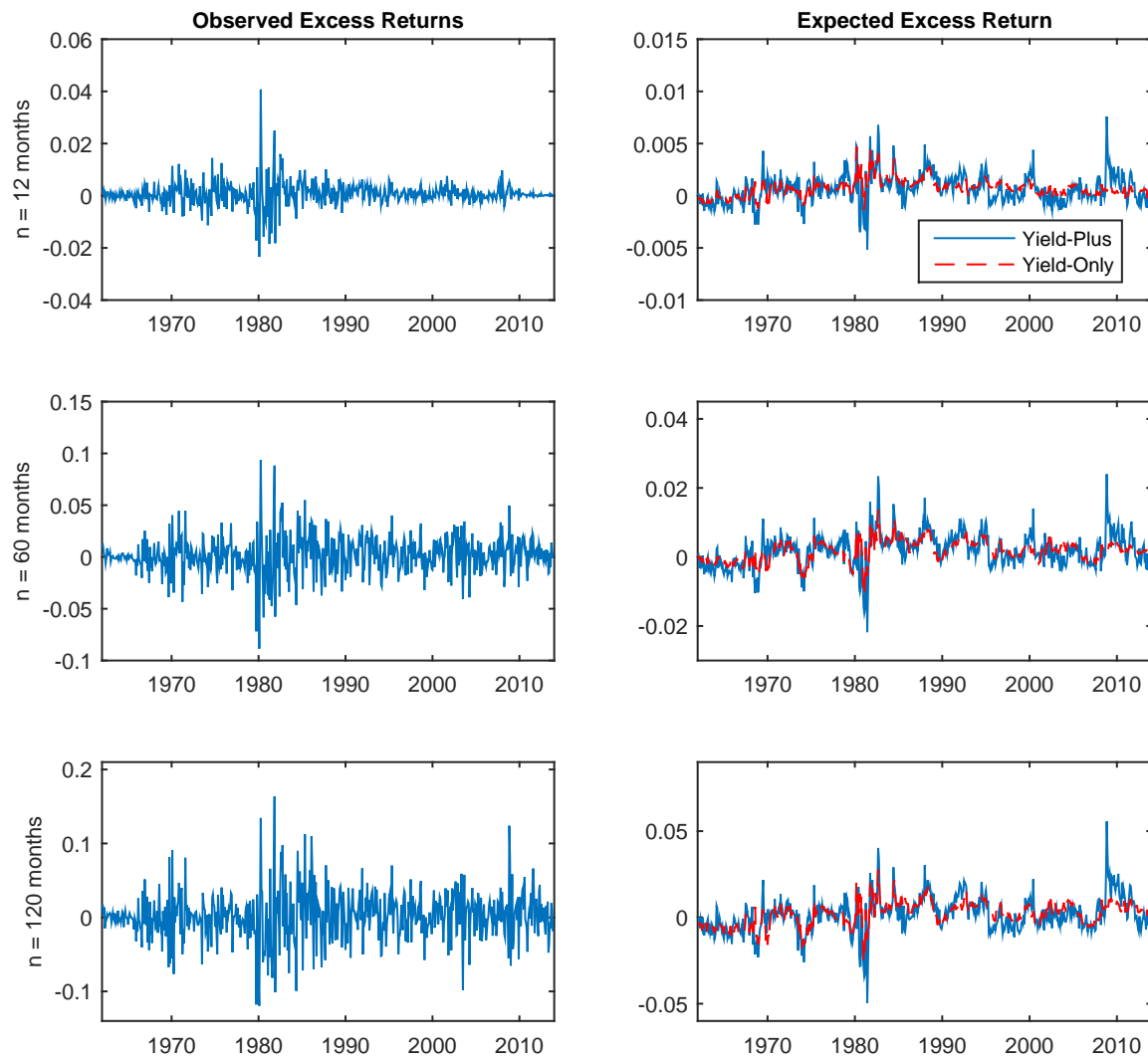
Notes: This figure plots the model implied loadings for yields and excess returns. The upper panel shows the loadings ($b_n = -\frac{1}{n}B_n$) for yields across 12 to 120-month maturities. The lower panel plots the loadings ($B'_n\lambda_1$) for expected one month holding period excess returns for the same maturities. Factors are the first five principal components of Treasury yields. Sample period is from 1962:01 to 2013:12.

Figure 3-11: Factor Loadings with Confidence Intervals (Yield-Only model)



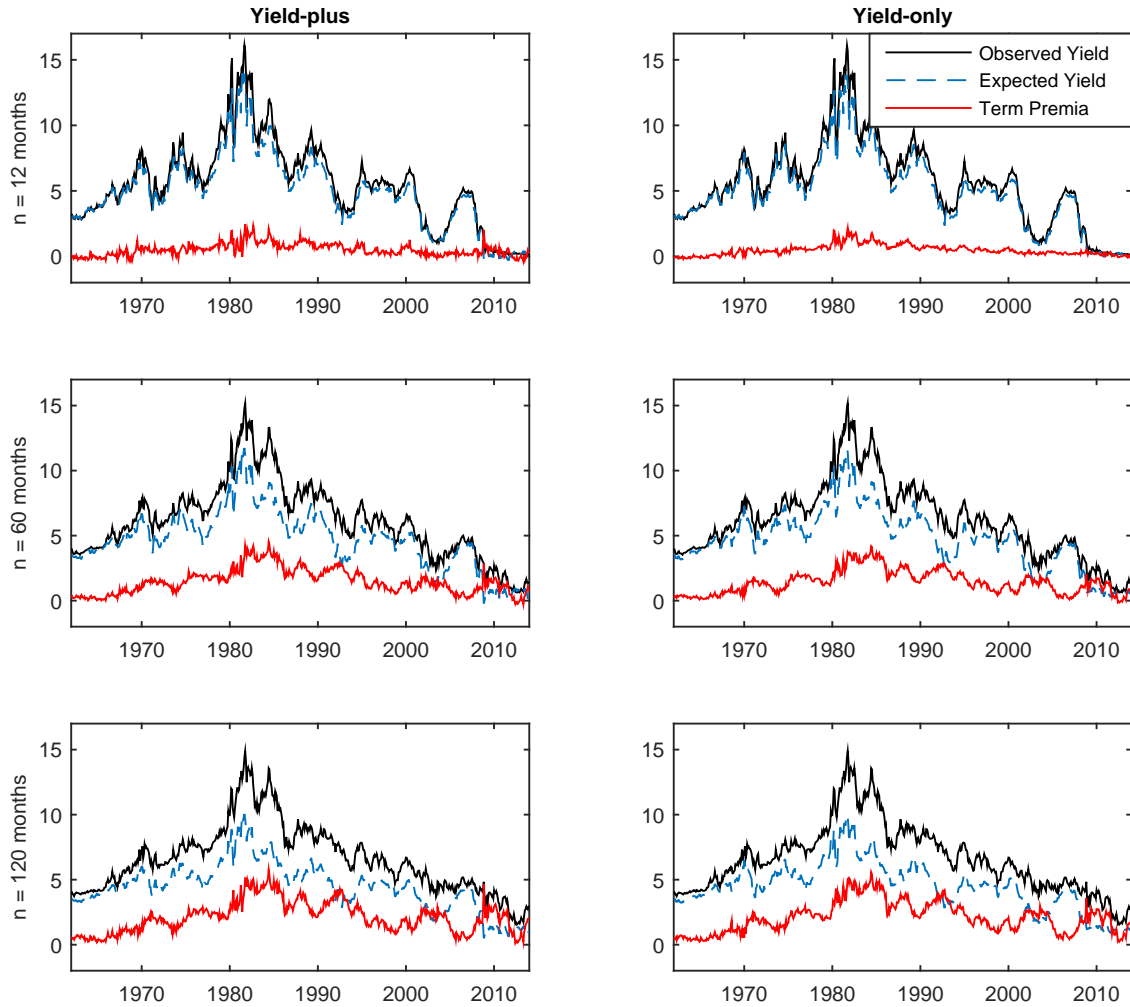
Notes: This figure plots the model implied loadings for excess returns with 90% confidence intervals for the factor loadings. Confidence intervals are calculated using a bootstrap procedure introduced by Malik and Meldrum (2016) with 10,000 replications. Factors are the first five principal components of Treasury yields. Sample period is from 1962:01 to 2013:12.

Figure 3-12: Observed and Expected Returns



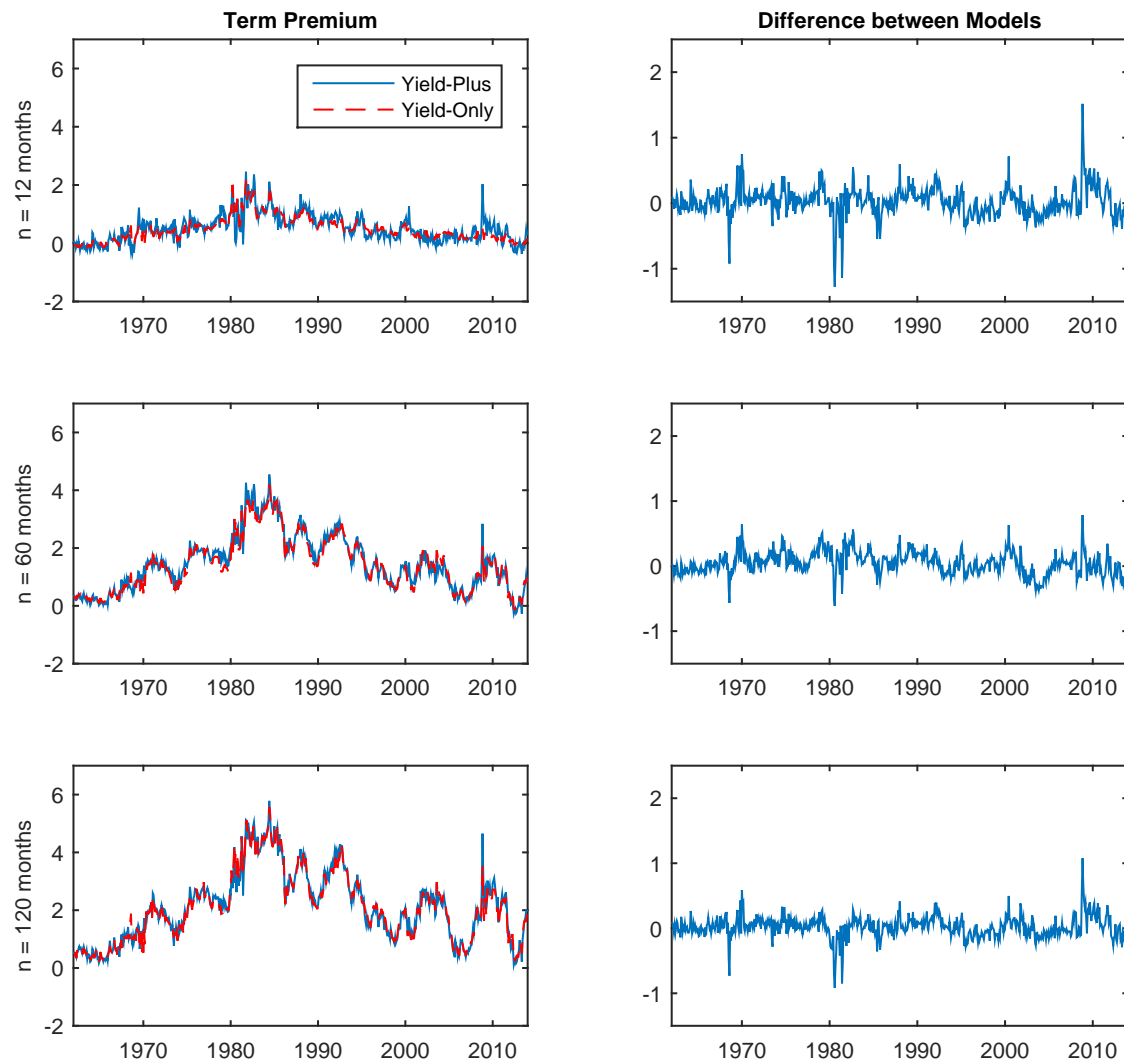
Notes: This figure plots excess holding period returns for 12, 60, and 120-month maturities. The left column shows observed excess returns and the right column shows model implied expected excess returns. The solid lines plot the expected excess return estimated using Yield-Plus model with the factors comprising the first three principal components of Treasury yields, Cochrane and Piazzesi (2005)'s monthly return forecasting factors, and the index of Economic Policy Uncertainty constructed by Baker et al. (2016). The dashed lines plot the expected returns estimated using Yield-Only model with the factors of the first five principal components of Treasury yields. Sample period is from 1962:01 to 2013:12.

Figure 3-13: Expected Yields and Term Premia



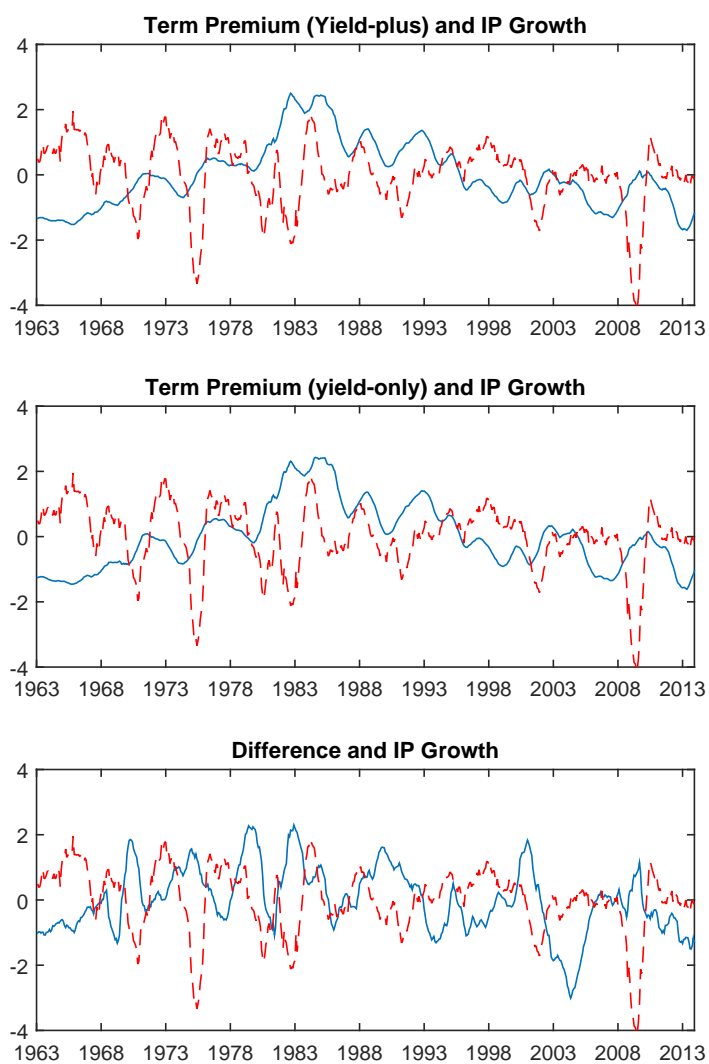
Notes: This figure plots observed yields (solid lines), model implied expected yields (dashed lines) and term premia (solid lines below) for 12, 60, and 120-month maturities. The two components of yields in the left column are estimated using Yield-Plus model and those of in the right column are estimated using Yield-Only model model. Yield-Plus model uses the factors comprising the first three principal components of Treasury yields, Cochrane and Piazzesi (2005)'s monthly return forecasting factors, and the index of Economic Policy Uncertainty constructed by Baker et al. (2016). The Yield-Only model uses the factors of the first five principal components of Treasury yields. Sample period is from 1962:01 to 2013:12.

Figure 3-14: Term Premium Estimates



Notes: This figure plots model implied term premia for 12, 60, and 120-month maturities. In the left column, the solid line plots the term premia estimated using yield-Plus model and the dashed line plots the term premia estimated using Yield-Only model. Yield-Plus model uses the factors comprising the first three principal components of Treasury yields, Cochrane and Piazzesi (2005)'s monthly return forecasting factors, and the index of Economic Policy Uncertainty constructed by Baker et al. (2016). The Yield-Only model uses the factors of the first five principal components of Treasury yields. The right column plots the difference of the estimated term premia between the two models. Sample period is from 1962:01 to 2013:12.

Figure 3-15: Term Premium and Industrial Production Growth



Notes: This figure plots compare two term premia estimates for 60-month maturity from Yield-Plus and Yield-Only models with industrial production growth. The solid line of the figure in the third row illustrates the difference of model implied term premia (Yield-Plus—Yield-Only). The dashed lines are monthly industrial production growth. All the series are the 12-month moving averages of the corresponding data and are standardised for easier comparison.

Matlab codes for Chapter 3

```

%% Load Gurkaynak-Sack-Wrghat US Treasury Yield (1961.6-2015.12)
load('gswdataall.txt')
[data,dates] = daymonthfuntion(gswdataall);
data = data./100;

%% Estimation Period
data = data(8:end-24,:);
dates = dates(8:end-24,:);
time = (1962+1/12:1/12:2014)';
mu01 = mean(data);
std01 = std(data);

%% Extract the PCA from the data
data3 = data(:,3:end);
[coeff,score,latent,tsquared,explained,mu] = pca(data3);

%% Estimate Factor Var using five PC
global k;
k = 5;
X = score(:,1:(k-2))';
Xmean = mean(X')';
Xstd = std(X')';
XX = (X-Xmean*ones(1,size(X,2)))./(Xstd*ones(1,size(X,2)));
XX = [XX(1,:); -XX(2,:); XX(3,:)];

%% Data of Log Bond Price
maturities = [1/12:1/12:10];
price = -data.*(maturities'*ones(1,size(data,1)))';
pr = price(1:end,1:end);

%% Short rate from Fama-Bliss CRSP file
load('ffm196106.txt')
shortrate = ffm196106(8:end-24,4)./100;

%% Excess Return Calculation
hprm1 = [pr(2:end,1:end-1)-pr(1:end-1,2:end)];
rxm1 = [hprm1-shortrate(1:end-1,1)*ones(1,(size(pr,2)-1))];
rxm1mean = mean(rxm1)';

%% EPU Historical Index from 1900
load('pu62.txt')
pu62 = pu62(1:end,:)./100;
pu62mean = mean(pu62); pu62std = std(pu62);
pu62level = ((pu62(:,1)-
pu62mean(1,1)*ones(size(pu62,1),1))./(pu62std(1,1)*ones(size(pu62,1),1)))';

```

```

%% Build CP Factor on monthly excess return
maturity_sel1 = [12,24,36,48,60,72,84,96,108,120];
pr_y = pr(:,maturity_sel1);
forward = pr_y(:,1:end-1)-pr_y(:,2:end);
forward = [data(:,12), forward];
forward = forward(1:end-1,:);
rxm2 = rxm1(maturity_sel1-1,:);
gammaF = zeros(size(rxm2));
betaOne = zeros(size(maturity_sel1,2),size(maturity_sel1,2));
for i=1:size(rxm2,2)
    [gammaF, beta1] = ols4(rxm2(:,i),forward);
    gammaF(:,i) = gammaF;
    betaOne(i,:) = beta1;
end

[CPMcoeff,CPMscore,CPMlatent,CPMtsquared,CPMexplained,CPMmu] = pca(gammaF);
CPM = CPMscore(:,1)';
CPMmean = mean(CPM');
CPMstd = std(CPM');
CPM = (CPM-CPMmean*ones(1,size(CPM,2)))./CPMstd;

%% Factor Transition VAR(1)
XX = [XX(:,1:end-1); CPM; pu62level(:,1:end-1)];
[mutrans,PI,V,SIGMA] = factorvar1(XX);

%% Select Maturities for rx Equation
maturity_sel2 = [5,11,17,23,29,35,41,47,53,59,83,119];
rxs = rxm1(maturity_sel2,1:end-1);

%% Excess Return Equation Estimation
[a,c,BETA,beta,betastar,E,sigma_sq]=rxequation(rxs,V,XX);

%% Price of Risk Parameter
lambda0 =
inv(beta*beta')*beta*(a+0.5*(betastar*SIGMA(:)+sigma_sq*ones(size(maturity_sel2,2),1)));
lambda1 = inv(beta*beta')*beta*c;

%% Short Rate Equation Estimation
[delta0,delta1,epsilon,sigma_epsilon_sq]=ols(XX,shortrate(1:end-1,:));

%% Estimated Term Structure using Affine Model
A = zeros(1,121);
B = zeros(k,121);

for i = 1:120
    A(1,i+1) = A(1,i)+B(:,i)'*(mutrans-
lambda0)+0.5*(B(:,i)'*SIGMA*B(:,i)+sigma_sq)-delta0;

```

```

        B(:,i+1) = (PI-lambda1)'*B(:,i)-delta1';
    end

    A = A(1,2:end);
    B = B(:,2:end);
    N = ones(1,120)./[-1/12:-1/12:-10];
    price_e = [A'*ones(1,size(XX,2))+B'*XX]';
    yield = bsxfun(@times,N, (A'*ones(1,size(XX,2))+B'*XX)');

    A0 = zeros(1,121);
    B0 = zeros(k,121);
    lambda00 = zeros(k,1);
    lambda10 = zeros(k,k);

    for i = 1:120
        A0(1,i+1) = A0(1,i)+B0(:,i)'*(mutrans-
        lambda00)+0.5*(B0(:,i)'*SIGMA*B0(:,i)+sigma_sq)-delta0;
        B0(:,i+1) = (PI-lambda10)'*B0(:,i)-delta1';
    end

    A0 = A0(1,2:end);
    B0 = B0(:,2:end);
    N = ones(1,120)./[-1/12:-1/12:-10];
    yield_exp = bsxfun(@times,N, (A0'*ones(1,size(XX,2))+B0'*XX)');

    %% Model Implied Risk Premia
    TP = yield-yield_exp;

    %% Excess Return - Actual and Fitted
    rx_e = B(:,1:end-1)'*(lambda0*ones(1,(size(X,2)-2))+lambda1*XX(:,1:end-
    1))+B(:,1:end-1)'*V;
    rx_e_inno = B(:,1:end-1)'*V;
    convexity=zeros(119,1); autonum = 10;
    for i=1:119
        convexity(i,1) = B(:,i)'*SIGMA*B(:,i)+sigma_sq;
    end

    rx_e_ep = B(:,1:end-1)'*(lambda0*ones(1,(size(X,2)-2))+lambda1*XX(:,1:end-
    1))-0.5*(convexity*ones(1,size(X,2)-2)); % Expected Excess Return
    rx_e = rx_e-0.5*(convexity*ones(1,size(X,2)-2));

    %% Bootstrapping
    NORep=10000;
    XXr=[]; Vr=[]; rxsr=[]; epsilon_r=[]; shorttrater=[]; arm=[]; betarm=[];
    crm=[];
    for h=1:NORep
        for t=1:size(rxs,2)
            pos1=fix(rand(1,1)*(size(XX,2)))+1;

```



```

XXr(:,1)=XX(:,pos1);
pos2=fix(rand(1,1)*(size(V,2)))+1;
Vr(:,t)=V(:,pos2);
XXr(:,t+1)=PI*XXr(:,t)+Vr(:,t);
pos3=fix(rand(1,1)*(size(rxs,2)))+1;
Er(:,t)=E(:,pos3);
pos4=fix(rand(1,1)*(size(rxs,2)))+1;
epsilon_r(:,t)=epsilon(:,pos4);
shortrater(:,t)=delta0+delta1*XXr(:,t)+epsilon_r(:,t);
end
rxsr=a*ones(1,size(rxs,2))+beta'*Vr+c*XXr(:,1:end-1)+Er;
[mutransr,PIr,Vr,SIGMAr] = factorvar1(XXr);
[ar,cr,BETAr,betar,betastarr,Er,sigma_sqr]=rxequation(rxsr,Vr,XXr);
arm(:,h) = ar;
betarm(:,h) = betar;
crm(:,h) = cr;
[delta0r,delta1r,epsilon_r,sigma_epsilon_sqr]=ols(XXr(:,1:end-1),shortrater(1:end,:));
end

crm_con_bot = quantile(crm,0.05,3)*100;
crm_con_top = quantile(crm,0.95,3)*100;

```

Chapter 4

High-Frequency Financial Information and Macroeconomic Forecast Revision

4.1 Introduction

The prediction of the future economic activity is of great interest for individuals and policy makers, as the expectations of market participants influence economic activities. Policy makers in Central Banks and governments produce forecasts of the main macroeconomic variables upon which they base monetary and fiscal policy responses, at the same time the published predictions provide useful information for economic agents making everyday economic decisions. Among various sources of economic predictions, the surveys of professional forecasters, comprising survey respondents' economic predictions over several macroeconomic and financial variables, are widely reported in the media and monitored by the policy makers as they

represent agents' expectations of future economic developments. The popularity of the forecast surveys may be because of the merit of the surveys that integrate a number of individual forecasters' predictions and also because of their regular updates, usually published on a monthly or quarterly basis, which can be taken as revisions of expectations.

The survey results are generally released as a form of consensus (for example, the average value of individual forecasts), without specifying the identification of the panellists and the prediction methods that they are built upon. Through a sequence of updating surveys, forecasters make and revise their forecasts by reflecting on the actual outcomes of the data and incorporating newly available information. This structure of the economic surveys, encompassing the initial forecast and following their updates, has initiated a large literature examining the expectations formations process and indicated the failure of full-information rational expectations hypothesis in survey forecasts.

The literature on economic surveys has focused on testing the accuracy, unbiasedness and efficiency of forecasts. The study of forecast efficiency goes back at least to Nordhaus (1987), who has demonstrated the failure of forecast efficiency by showing forecast errors and revisions are correlated with past forecast revisions. Forecast efficiency has been tested in numerous studies and most of them have manifested the failure of the weak form of forecast efficiency in consensus forecasts (see, for example, Isiklar et al. 2006; Ager et al. 2009; Capistrán and López-Moctezuma 2014) and also in individual level forecasts (Gallo et al. 2002; Doornik and Wessier 2011; Deschamps and Ioannidis 2013; Andrade and Le Bihan 2013). With only a few exceptions such as Clements (1997), most studies have found significant positive coefficients on lagged revisions, implying that forecasters do not update their forecasts sufficiently when new information is received.

Sluggish updates of survey forecasts have recently gained much attention in the literature testing models of information rigidities using data from surveys of professional forecasters. Coibion and Gorodnichenko (2012, 2015a), for example, analyse the relation between ex-post mean errors in consensus forecasts and ex-ante forecast revisions within a framework of imperfect information models comprising sticky (Mankiw and Reis 2002) and noisy information (Woodford 2001; Sims 2003), operating subject to information frictions. Doovern et al. (2015) examine information rigidities in real GDP growth forecasts in individual forecasts using a test proposed in Nordhaus (1987) and shows the forecasters' behaviour in smoothing updates is more in line with the predictions of the noisy information model.¹

Instead of testing the informational rigidities in survey forecasts using only the test of weak form efficiency (Nordhaus 1987), in this paper we directly examine how forecasters incorporate information from financial markets as they make predictions at both the consensus and individual levels. Specifically, we explore whether forecasters revise their predictions of GDP growth by responding to changes in credit spreads and test whether they are consistent with the relations that theory and empirical studies imply. We use the survey Forecasts data set for the US by Consensus Economics, which comprises monthly predictions made by a panel of professional forecasting institutions.

To use high-frequency financial market data in a model explaining low-frequency forecast revisions, we adopt a framework of mixed data sampling (MIDAS) proposed by Ghysels et al. (2004, 2007). The MIDAS regression enables us to relate variables with different frequencies by reducing the number of parameters to estimate, by using weighting functions with only a few hyper-parameters, such as

¹More studies examining the information rigidities with survey forecasts include Dräger and Lamla (2012), Andrade and Le Bihan (2013), Loungani et al. (2013), and Hur and Kim (2016) among others.

distributed lag polynomials.

The studies applying the MIDAS framework initially focused on financial applications especially predicting volatility in financial asset prices (see Ghysels et al. 2007; Alper et al. 2008, Chen and Ghysels 2010; among others). The method has recently been applied to improving forecasts of low-frequency macroeconomic variables, such as GDP growth, with the aid of higher frequency macroeconomic and financial data. For instance, Clements and Galvão (2008) demonstrate a significant reduction in RMSE by using monthly indicators in a MIDAS specification to forecast quarterly output growth compared quarterly AR or AR distributed-lag (ADL) models using only quarterly series. Andreou et al. (2013) incorporate information from daily financial data in forecasting quarterly GDP. They first extract financial factors from a large dataset of daily financial asset prices and use these factors in MIDAS regressions demonstrating that adding high-frequency financial information to the model delivers superior forecasting performance.²

There are two reasons for using high-frequency daily asset prices with MIDAS framework in our study. First, even though the information sources and methodologies that the survey forecasts built upon are largely unknown, it is reasonable to expect that forecasters updating their forecasts in short intervals (in our case monthly basis) will endeavour to incorporate information from high-frequency economic news. As financial asset prices are forward-looking in nature and summarise expectations over future economic activity, the prices of financial asset reflect all the high-frequency information in a timely manner. The common methods of time-aggregating higher-frequency variables, such as averaging or taking only the latest

²More articles linking low-frequency (quarterly or monthly) macroeconomic series with high-frequency (monthly or daily) macroeconomic or financial data include Schumacher and Breitung (2008), Hamilton (2008), Armesto et al. (2009), Marcellino and Schumacher (2010), Kuzin et al. (2011), Monteforte and Moretti (2013), Modugno (2013), Galvão (2013), Foroni and Marcellino (2014), Breitung and Roling (2015).

value, may result in loss of efficiency using past information.

Second, due to the obscureness in the timing of the surveys, a priori aggregation schemes summarising the high-frequency data may ignore respondents' forecast behaviour in forming predictions upon arrival of newly available information. Indeed, as discussed in Ghysels and Wright (2009), there may exist gaps among the day when the forecasters information set are formed, the day when the survey are actually submitted, and the day set as the submission deadlines.³ The adoption of MIDAS regression resolves these issues, as it relies on a flexible aggregation function with minimal restrictions, allowing a data-generated weighting scheme (see Andreou et al. 2010 for a detailed discussion).

Our study is related to a large body of literature on the predictive information in financial asset prices for future economic activity.⁴ For example, in the tradition of Estrella and Hardouvelis (1991), the ability of spreads between long- and short-term government bonds to predict output growth and recession has been regarded as one of the stylised facts among economists (see also Harvey 1989, Stock and Watson 1989, Dotsey 1998, Wright 2006, Ang et al. 2006, Rudebusch and Williams 2009, among many others).⁵

³We know the deadline for each survey, which do not exactly match to the day the forecasters made their forecast and answered the survey.

⁴Stock and Watson (2003) provide a comprehensive survey on the role of asset prices forecasting macroeconomic variables. They find that asset prices work generally as useful indicators predicting economic activity, but the predictive ability of individual indicators is unstable over time.

⁵Term spread (slope of Treasury yield curve) and credit spread are regarded as most informative indicators forecasting economic output. A reduction in forecasting power in term spread has found in the studies such as Gertler and Lown (1999), Mody and Taylor (2004), and Wheelock and Wohar (2009), whereas studies like Rudebusch and Williams (2009) show that a simple model using only yield spreads provide better forecasts compared to the professional forecasts at predicting recessions. Gertler and Lown (1999) state that the changes in the conduct of monetary policy in the early 1980s may account for the deterioration of the forecasting ability of the term spread.

The recent financial crisis has brought more attention to the potential role of financial frictions in amplifying the effect of macroeconomic shocks. The payment of a premium, by firms wishing to invest, for accessing external finance is a key concept for the financial accelerator models of Gertler and Gilchrist (1994) and Bernanke et al. (1994, 1999) explaining a sharp and long-lasting deterioration in economic activity from a financial crisis. More recent theoretical work by Philippon (2009) emphasises the relative price between corporate and Treasury bonds in determining the value of q , an equivalent measure of Tobin (1969)'s q constructed with bond prices, providing further insight into the role of credit spreads in anticipating output fluctuations.

A large empirical literature has shown that credit spreads have predictive power for real activity. Gertler and Lown (1999) and Mody and Taylor (2004) show that credit spreads based on high-yield corporate bonds forecast US GDP growth. However, more recently, Gilchrist et al. (2009) test a variety of credit spreads for forecasting economic activity and document that the predictive power of credit spreads is more prominent using corporate bonds of intermediate-risk rather than high-risk firms. The most recent works by Gilchrist and Zakrajšek (2012), Faust et al. (2013), Krishnamurthy and Muir (2015), and Bleaney et al. (2016) support the earlier findings that credit spreads have substantial predictive content, and a component in credit spreads attributing to deviations from the usual compensation on expected defaults strongly predicts a decline in economic activity.

Our paper is also linked to the growing interest in recent studies examining the difference in forecasting behaviour under different states of the business cycle.⁶ For instance, Coibion and Gorodnichenko (2015b) test information rigidity across

⁶More exercises examining state-dependent forecast errors include Sinclair et al. (2010), Sheng and Wallen (2014), Messina et al. (2015), Xie and Hsu (2016), and El-Shagi et al. (2016).

business cycle fluctuations and find that the degree of information rigidity decreases in recessionary periods. Loungani et al. (2013) finds that the rigidity in forecast revisions is much lower in recessions than in normal years. Dovern and Jannsen (2017) analyse the forecast bias according to the phase of business cycles and find that the forecasts errors turn positive as the economy recovers from recessions and disappear during expansions, implying a differential treatment of information across the cycle.

Our findings can be summarised as follows. First, an increase in daily credit spreads, the difference between the yields on an index of seasoned long-term Aaa-rated corporate bonds and the constant maturity 10-year Treasury, forecasts significant negative revisions in consensus forecast revisions of US GDP growth. The weighting functions associated with MIDAS regression indicate clear hump-shaped polynomials which is consistent with the theoretical prediction in the models of information rigidities (Coibion and Gorodnichenko 2012; 2015a). Testing the relations in individual forecast level, we find that forecasters broadly agree in the direction of the revisions as they update their information set using the news from financial asset prices.

Second, we find that individual forecasters update their GDP forecast quite frequently and that forecast smoothing at an individual level is significantly lower than that measured using consensus forecasts.⁷ Although the size and significance of the response are different across individual forecasters, most individual forecasters (more than 90%) revise their forecast downwards as daily credit spread increases, demonstrating that they systematically update their forecast, at least in terms of the direction of revisions, consistently with the predictions of the theory.

⁷Dovern et al. (2015) show similar results that information rigidity in the average forecast is substantially higher than that in individual forecasts.

The weighting functions in individual level MIDAS regressions show similar hump-shaped weights, as is in the consensus-level exercise, indicating individual forecasters are also slow in incorporating high-frequency information in financial asset prices. We interpret this result as showing that the expectations formation behaviour of forecasters is more related to the implications of noisy information (Woodford 2001; Sims 2003) rather than those of sticky information models (Mankiew and Reis 2002).

Third, we provide evidence as to whether forecasters have state-dependent forecasting behaviour for revising GDP predictions as they incorporate new information from financial asset prices. Proxying the state of the economy using a real-time daily measurement of business conditions built by Aruoba et al. (2009), we find that the effect of credit spreads on revisions of output growth forecasts is more prominent during bad economic states. The responses of the forecasters to credit spreads are faster under such economic conditions, which is consistent with the findings of Gorodnichenko (2008) that information rigidity is endogenous to the state of the economy and that the inattention to macroeconomic developments by economic agents decreases in the presence of large macroeconomic shocks.

The rest of the paper is organised as follows: Section (4.2) explains the structure of Economic Consensus and other data. Section (4.3) explains MIDAS methodology for analysing mixed frequency data. Section (4.4) discusses the empirical findings regarding the effect of credit spreads on forecast revisions. Finally, Section (4.5) concludes.

4.2 Data

4.2.1 Consensus Economics

We examine the effect of credit spreads on GDP forecast revisions using the Consensus Economics data set. Every month, Consensus Economics Inc. publishes macroeconomic forecasts provided by a panel of professional forecasters comprising financial institutions, research centres and large industrial firms. We use the fixed-event GDP forecasts for the United States between 1991 and 2016. Panellists predict GDP both for current and the following year every month, i.e. each forecaster makes the initial forecast on a target year on January of the previous year and renews the forecast, that makes the total number of forecasts for a target year up to 24. This fixed-event structure of the survey gives a three-dimensional panel structure (formalised by Davies and Lahiri 1995), comprising 26 target years, 24 forecast horizons, and N forecasters. Figure (4-1) illustrates how the participation of the panellists in Consensus Economics evolved over the sample period from 1991 to 2016. As characterised by Capistrán and Timmermann (2009), forecasters frequently enter, exit, and reenter with a period of absence. The average number of submitted forecasts in each survey is 26.0 for both current and the following year, which makes 16,213 observations in total.

Calculating the revisions, we only count the differences between consecutive revisions, but consider submitted but unchanged forecasts as zero revisions.⁸ To prevent the inclusion of non-consecutive forecast values calculating consensus revi-

⁸There are chances that forecasters do not respond as their predictions do not change. Dovern and Wessier (2011) interpolate the data when an observation is missing but two adjacent forecasts are the same by setting the missing value with the adjacent value. We tried the interpolation and confirmed that increasing observation with the interpolation does not affect our main findings.

sions, we first calculate individual revisions, and then average the revisions across the individual forecasts.⁹ Each target year has 24 forecasts thus 23 revisions in maximum.

Figure (4-2) illustrates the means and standard deviations of individual forecast revisions across revision horizons ($h = 23, 22, \dots, 1$). The plots in the first row show that forecasters made positive forecast errors on average during sample period. The error is mostly corrected during the second half of the first year. For instance, GDP forecast for a certain year begins with somewhat optimistic number in January of the previous year, but the bias is reduced as they lower the forecast between July and December before the target year begins. The average standard deviation of revisions among forecasters, however, increases when the individual forecasts are under active revisions. Entering the current year, the disagreement in revisions diminishes along with decreasing horizons.

Matching monthly revisions with daily credit spread data, we take forecast revisions from 7th to 18th updates, as we expect the relationship between output forecasts and financial information should be most relevant.¹⁰ Dovern et al. (2015) find that the average size of revisions at mid-horizons are larger than those at very long or short forecast horizons. Sheng and Wallen (2014) also document that professional forecasters make forecast revisions most frequently in the medium term (10-17 months ahead) using the Consensus Forecasts.¹¹

⁹For preventing the problems coming from small individual observations, several literature (such as Dovern and Weisser 2011; Deschamps and Ioannidis 2013) eliminate the forecasts who do not participate enough. Occasional participation may produce outliers in forecasts. As we only consider the revisions rather than the values of forecasts, we include all the forecasters as calculating consensus forecasts, regardless of the forecasters' participation rates. However, the results are robust even when we exclude the forecasters with only small number of participation.

¹⁰Testing the relations with different sets of forecast horizons, such as the first 12 or the last 12 revisions, however, gives qualitatively the same results (results are available on request).

¹¹Sheng and Wallen (2014) explain that forecasters' inattentiveness at very long and short forecasting horizons is due to noisier signals and the observation of actual outcomes, respectively.

4.2.2 Credit Spreads

Credit spreads (also called the quality spread or default spread) are the difference between the interest rates on matched maturity debt with different default risk. The predictive content of credit spreads has been examined in a number of articles focusing on the US economy where the private debt market is most active. For example, Bernanke (1983) documents the Baa-Treasury bond spread worked as a useful indicator predicting industrial production growth during the Great Depression. Guha and Hiris (2002) show the same spread leads economic activity and contains useful information about the turning points of the business cycles between 1925 and 1999. The spread between commercial paper and Treasury bills (paper-bill spread) also has been shown as a significant predictor of real growth (see, for example, Stock and Watson 1989; Friedman and Kuttner 1993; Emery 1996; Ewing et al. 2003; Bordo and Haubrich 2004), and Getler and Lown (1999) show the high yield-spread, additional compensation for holding below-investment-grade corporate bonds, outperforms other financial indicators.¹²

We obtain daily observations of interest rates and credit spreads from FRED (Federal Reserve Economic Data). The credit spread is calculated as the difference between Moody's seasoned Corporate Bond and 10-year Treasury constant maturity. By the preliminary MIDAS regression exercises based on different measures of credit spreads from the literature,¹³ we choose the spread between Aaa-rated corporate bond and 10-year Treasury Note (Aaa-spread) as our main high-frequency financial variable, as it has shown the most significant effects on forecast revisions.

¹²Compared to corporate-Treasury spreads, the spreads across corporate bond categories (such as High yield-Aaa and Baa-Aaa) are mostly related to default risk premia, thus their relationship with business cycle is concentrated during recessions (Duca 1999).

¹³Baa-spread, High-yield spread, and 10-year Treasury rate are shown to predict forecast revisions, but Aaa-spread shows more significant and robust results.

Figure (4-3) plots daily developments in interest rates of Aaa-rated Corporate bonds, 10-year Treasury Note, Aaa-spreads and its daily changes from 1991 to 2016. Both of the rates have shown decreasing trends, but the Aaa-spread has fluctuated markedly, widening notably around the early 2000s recession and the recent Great Recession.

The predictive power of the Aaa-spread has been tested in several recent studies (see Mody and Taylor 2004; Gilchrist et al. 2009; Mueller 2009; Buchmann 2011; Schumacher 2014). Specifically, Gilchrist et al. (2009) find that the forecasting ability of bond spreads is closely associated with information about bonds of intermediate-risk rather than those of high-risk firms.

4.2.3 Other Variables

As we attempt to test forecasters' different expectations formation incorporating financial information between different economic conditions, the identification of economic states is required. Literature testing state-dependent forecasting behaviour (for example, Sinclair et al. 2010, 2015; Dovern et al. 2012; Lougani et al. 2013; Messina et al. 2105) uses recessions identified ex-post by institutions such as National Bureau of Economic Research (NBER) or Economic Cycle Research Institute (ECRI). A notable exception is Dovern and Jannsen (2017) who identify recession years at annual frequency using the most recent data vintage.

Examining state-dependent forecasting behaviour based on an ex-post measure of the business condition may be problematic as forecasters do not know the state of the economy at the time they make forecasts.¹⁴ Instead of using ex-ante de-

¹⁴Determining the recessionary periods, matching ex-post identified recession months between the actual survey date or the target year is also questionable.

financed recessions, we adopt a real-time measure of business conditions developed by Aruoba, Diebold, and Scotti. (2009, ADS index hereafter). The ADS index is constructed using a dynamic factor model incorporating various macroeconomic and financial business conditions indicators in diverse frequencies. The index is updated by the Federal Reserve Bank of Philadelphia and has been proven to be a useful economic indicator summarising the up-to-date information that economic agents receive in real time.¹⁵

We assume that forecasters decide the current economic state using all the available real-time information summarised in the ADS index. Then the economic states at each survey perceived by the forecasters are measured by the average values of the daily ADS index between the previous and current survey deadlines. The real-time economic activity measure matched to the monthly survey cycle is illustrated in Figure (4-4). The index is constructed to have zero mean, so positive (negative) values indicate that the economy is in better (worse) than average conditions. This method makes for a more transparent and straightforward rule which might be close to agents' recognition of the economic conditions, using a broad information set in real-time.

4.3 MIDAS Regressions

MIDAS regression is a framework that involves data sampled at different frequencies. Applying parsimonious but flexible distributed lag polynomials, the MIDAS framework allows us to use the information in high-frequency explanatory variables, avoiding probable issues from an a priori data aggregation scheme.¹⁶ Our

¹⁵The index can be accessed online at <https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index>.

basic MIDAS model predicting forecast revisions is given by

$$REV_{t+1,\tau} = \alpha + \beta B(L^{1/m}; \boldsymbol{\theta}) CS_t + \rho REV_{t,\tau} + \varepsilon_{t+1}, \quad (4.1)$$

where $REV_{t,\tau}$ denotes a consensus forecast revision for US GDP growth rates for target year τ at time t . Consensus forecast revisions are calculated as the average of individual forecast revisions, i.e. $REV_{t+1,\tau} = (1/n_t) \sum_i^{n_t} REV_{i,t+1,\tau}$ with n_t , the number of survey respondents at time t .

Individual forecast revisions are the differences between two consecutive GDP growth forecasts of individual i for target year τ at time t . Specifically, $REV_{i,t+1,\tau} = F_{i,t+1,\tau} - F_{i,t,\tau}$, where $F_{i,t,\tau}$ is individual i 's forecast of GDP growth rate.¹⁷ CS_t is the daily change in credit spreads. Our model specification is in the class of ADL-MIDAS regressions, introduced by Andreou et al. (2013), offering the structure of ADL (Augmented Distribution Lag) regression with mixed frequency data. The inclusion of an autoregressive term of order one is from the literature testing the weak form of forecasting efficiency (Nordhaus 1987; Deschamps and Ioannidis 2013; Doornik et al. 2015).

The function $B(L^{1/m}; \boldsymbol{\theta}) = \sum_{k=1}^K b(k; \boldsymbol{\theta}) L^{k/m}$ selects the weighting scheme for high-frequency data, where $L^{k/m} CS_{t-1} = CS_{t-1-k/m}$. K denotes the number of the lagged high frequency explanatory variables, and m is the number of trading days in a month. Several previous studies proposed diverse functional forms of MIDAS polynomial weights aiming at parsimonious but flexible specifications.¹⁸ In this

¹⁶For survey on MIDAS regression framework, see Armesto et al. (2010), Andreou et al. (2011), and Foroni and Marcelliono (2013).

¹⁷Notations for the revision horizons (h) are abstracted as each forecast time (t) matches to one corresponding consensus revision.

¹⁸Ghysels et al. (2007) present a discussion on various lag structures to parameterise MIDAS weighting functions.

study, we employ four weighting schemes to test the robustness of the relations across different methods.

The first weighting scheme we consider is the normalised beta probability density function suggested by Ghysels et al. (2004, 2007). Specifically, we use

$$b(k; \theta_1, \theta_2) = \frac{x_k^{\theta_1-1} (1-x_k)^{\theta_2-1}}{\sum_{k=1}^K x_k^{\theta_1-1} (1-x_k)^{\theta_2-1}}, \quad (4.2)$$

where $x_k = k/(K+1)$. Our second weighting scheme uses Almon lag polynomial of order P , specified as

$$\beta b(k; \theta_0, \dots, \theta_P) = \sum_{p=0}^P \theta_p k^p. \quad (4.3)$$

We also use two alternative polynomial specifications; Step-Weighting and U-MIDAS. The step-function allocates different coefficients on several intervals of high frequency data such as

$$\beta b(k; \theta_0, \dots, \theta_P) = \theta_1 I_{k \in [a_0, a_1]} + \sum_{p=2}^P \theta_p I_{k \in (a_{p-1}, a_p]}, \quad (4.4)$$

where P is the number of steps, $a_0 = 1 < a_1 < \dots < a_P = K$. I_k is an indicator which becomes 1 when k belongs to its corresponding interval and 0 otherwise. Meanwhile, unrestricted MIDAS polynomials (U-MIDAS) use a simple regression estimating the individual coefficients without any constraints.¹⁹

¹⁹U-MIDAS is particularly useful when m (the number of high-frequency data linked to one low-frequency observation) is small, especially in the case of regressing quarterly series on monthly (Forni et al. 2015). However, we estimate U-MIDAS model to confirm whether we can find a specific daily lag formation as the forecasters use financial information.

4.4 Empirical Results

4.4.1 Credit Spread and Growth Forecasts Revisions

As discussed in the first section, theoretical and empirical studies have shown that increasing credit spread affects GDP growth negatively. We estimate the four MIDAS regressions introduced in the previous section to test for the relation between credit spread and forecast revisions. Our sample begins with the first forecast revision in 1991M01 for the growth rate of 1991 and ends with the revision in 2016M06, which makes the total number of 306 revisions. The number of Aaa-spread is 6,505 for 26 years, giving 20.8 observations on average for each month. Trading days per month (m) and the number of lagged daily series (K) in Equation (4.1) are set to be 20. We have the submission deadline date, which is usually the second Monday of each month, so 20 daily observation of credit spreads before the survey deadlines are selected to match for each forecast revision.²⁰

As deterioration in credit conditions works to propagate and amplify the effects of macroeconomic shocks and depresses economic activity (Bernanke et al. 1999), we anticipate that survey respondents would make negative (positive) growth forecast revisions when credit spread increases (decreases). Furthermore, we expect no clear patterns on MIDAS weighting polynomials on daily information, as there is no reason that credit spreads on specific days in a month react more strongly to the future economic growth. A forecaster who is efficient in incorporating information from high-frequency asset prices may use every available observation by not using only lagged or most recent movements in credit spreads.

²⁰An exercise with a larger number of lagged daily spread, for example, 40 lags, gives similar results, as added lags do not affect the revisions significantly.

Figure (4-5) plots the estimated MIDAS weights for the four different weighting schemes. The models M1 and M2 show that consensus forecasts for US GDP growth rates are revised negatively when credit spread increases. Table (4.1) reports the estimated parameters for the M1 and M2 and the results using the model with only lagged revisions, denoted by M0. The slope for M1 is significantly negative, and the estimated parameters in the weighting functions are also significant. The estimate on the lagged revisions, representing forecast rigidity, is around 0.5 and highly significant implying that forecasters smooth their forecast revisions.²¹ The MIDAS estimations including daily credit spreads give substantially higher adjusted R^2 , implying that forecasters update growth predictions in line with the developments in credit conditions.

The weighting functions illustrate hump-shaped polynomials with their largest effects are concentrated between 10 and 15 days. The number of steps in model M3 (P) is set to four, so each step approximately matches a week before the submission deadlines. We report the coefficients for M3 and M4 in the bottom row of Figure (4-5) plotted with two standard errors. The estimated coefficients on the steps in M3 are negative for all four steps and show the largest impact for the third lagged step. Significant coefficient estimates of U-MIDAS (M4) are all negative but the effect is dominant between 12 and 18 daily lags.

The common pattern of the four weighting functions shows that forecast revisions are better associated with daily information lagged around two weeks prior to the submission deadlines rather than the latest information.²² This result indi-

²¹Our estimate of the rigidity parameter (ρ) is relatively larger than those from previous studies with different sample periods. For example, Ager et al. (2010)'s estimated rigidity coefficient is 0.28 based on the data from 1996 to 2006, and Dovern et al. (2015) report 0.33 using the sample from 1989 to 2010.

²²The survey deadline do not necessarily match the actual survey submission day or the day when the respondents form their predictions. However, we believe that professionals, who make

cates that the forecasters do not incorporate the totality of financial information received in equal measure, which makes them rely more on their prior beliefs embedded in previous forecasts, contributing to forecasters' under-reaction to new information.

4.4.2 Economic State and Forecast Revisions

The theoretical explanations for the sluggishness in survey forecasts have been proposed in several recent studies, for example, finding its source from information frictions (Coibion and Gorodnichenko 2012), heterogeneity in loss aversion (Capistrán and Timmermann 2009), and forecasters' rational behaviour maximising their perceived abilities (Deschamps and Ioannidis 2013).

The origins of the forecasts smoothness in these models, such as the variations in information rigidity and the effect of revisions determining perceived ability, in fact, should be closely related to economic conditions. For example, in periods of high volatility, forecasters may confront larger costs of ignoring new information as well as a smaller loss of reputations by deviating from their previous forecasts.

Following the recent literature studying state-dependent expectations formation in forecasting behaviour, we examine whether forecasters' responses to high-frequency information in asset prices differ according to the economic state. Specifically, our model modifying Equation (4.1) is

$$\begin{aligned} REV_{t+1,\tau} = & [\alpha_0 + \beta_0 B(L^{1/m}; \boldsymbol{\theta}_0) CS_t + \rho_0 REV_{t,\tau}] \times (1 - \hat{s}_{t+1}) \\ & + [\alpha_1 + \beta_1 B(L^{1/m}; \boldsymbol{\theta}_1) CS_t + \rho_1 REV_{t,\tau}] \times \hat{s}_{t+1} + \varepsilon_{t+1}, \end{aligned} \quad (4.5)$$

monthly predictions consecutively, may form their predictions on a day close enough to observe most up-to-date information.

where \hat{s}_{t+1} is a dummy variable associated with the ADS index determining economic states between t and $t + 1$. The value of \hat{s}_{t+1} is zero when the averaged ADS index is above or equal to a certain threshold and one otherwise. We set the threshold so that the months with the lowest one third of averaged ADS index to be identified as bad states. Determining the threshold, we consider the fact that the duration of economic cycles is usually longer for expansions than contractions. As illustrated in Figure (4-4), the identified bad states (bottom one third) include all the months defined as recessions by the NBER, but cover more times of economic slowdown due to smaller business cycles.²³

Figure (4-6) illustrates the means and standard deviations of individual forecast revisions across revision horizons ($h = 23, 22, \dots, 1$) calculated between only good and bad economic states. The plots in the first column show that forecasters made negative forecast errors in good states, whilst relatively large positive errors in bad states, implying that they initially made moderate forecast values without much knowledge of the future economic states. Revisions in bad states begin from the first revising month and the size of negative revisions peaks between 7th and 12th revisions, which is earlier than revisions in good economic states made between 10 and 16 months after the initial forecasts. However, as shown in the second column of the figure, the standard deviations of the revisions during those active revising months are larger in bad states, suggesting that forecasters disagree more in revising GDP forecasts under such economic conditions.

Figure (4-7) and (4-8) plot the estimated MIDAS weights using the four models. The effects of daily credit spread on monthly consensus forecast revisions are negative in both states, but the size of the relations are notably stronger in bad

²³However, the results of our exercises do not change qualitatively as we adjust the threshold or use alternative definitions such as NBER Business Cycle Dating.

states. Comparing the slope coefficients on credit spreads in the M1 specification, Table (4.2) reports that $\hat{\beta}_1$ is larger than $\hat{\beta}_2$ in absolute value. The coefficients of M3 and M4 show that growth forecast revisions are more prominent in bad economic states and forecasters incorporate more recent information associated with the variations in credit spreads. These results are consistent with the findings of Loungani et al. (2013) that the acquisition of information is faster during recessions. Gorodnichenko (2008) has also shown that macroeconomic shocks lower agents inattention over business cycles as information rigidity changes endogenously to economic states. The adjusted R^2 in bad states is 0.45 (M1) and 0.43 (M2) is higher compared to the R^2 from the regressions with only lagged revision (0.18), implying that forecasters respond much more to the information about credit conditions.

4.4.3 Forecast Revisions at Individual Level

In this subsection, we test whether the effect of credit spreads on GDP forecast revisions found in the consensus forecast level exist in individual forecasts. The individual MIDAS regression model analogous to Equation (4.1) is

$$REV_{i,t+1,\tau} = \alpha_i + \beta_i B(L^{1/m}; \boldsymbol{\theta}_i) CS_t + \rho_i REV_{i,t,\tau} + \varepsilon_{i,t+1}, \quad (4.6)$$

where $REV_{i,t,\tau}$ is forecast revision of forecaster i for target year τ at time t . Equation (4.6) have five parameters to estimate for each individual forecaster in case of M1. We only test with the forecasters who made more than 50 revisions in total, that leaves 41 forecasters with the average number of revisions across individuals is 148.9.

We report the results of individual level estimation using model M1 as it provides the slope estimates ($\hat{\beta}_i$) related to the sign and size of forecast updates associated with the developments of the credit spread. The estimated coefficients on the daily credit spread (β_i) are negative for 36 out of 41 (87.8%) individuals. Counting only significantly estimated coefficient at the 10% level, we find 28 (93.3%) among 30 individuals negatively responded to the change in Aaa-spread. The first row in Figure (4-9) plots the histogram of the estimated coefficients ($\hat{\beta}_i$), showing that the estimates are distributed conforming to the normal, with an average value -10.3, close to the value (-9.9) from the coefficient of consensus revisions ($\hat{\beta}$).

The estimates of individual forecast rigidity ($\hat{\rho}_i$) are between -0.40 and 0.52, and 37 out of 41 individuals are positive, supporting sluggish forecast updates even at an individual level. However, the rigidity measure on average is much lower (0.14) compared to the estimate of consensus forecast revision which is around 0.5. This result is consistent with the findings in previous studies that information rigidity in forecast surveys is a property largely related to the consensus forecast level and it is not as strong at an individual level (see, for example, Coibion and Gorodnichenko 2015a; Doornik et al. 2015). This exercise with individual forecast revisions shows that forecasters systematically revise their forecasts according to high-frequency information in asset markets, mostly agreeing on the possible impact of the developments in credit conditions, but they still allow inefficiencies in using the information as they do not fully react to the latest developments in financial asset prices.²⁴

We further examine individual forecasters behaviour updating their forecasts

²⁴Studies such as Gallo et al. (2002) have shown that the consensus made by other forecasters in the previous period affect individuals' current predictions. Our study is not directly connected to the issue, as we focus on the forecast revisions. However, our findings at individual level forecasters imply that revisions responding to the signals from the credit conditions make the forecasters' herding less severe, as the majority of the forecasters revise in the same direction.

differ between economic states. Our model adjusting Equation (4.6) is

$$\begin{aligned} REV_{i,t+1,\tau} = & [\alpha_{i,0} + \beta_{i,0}B(L^{1/m}; \boldsymbol{\theta}_{i,0})CS_t + \rho_{i,0}REV_{i,t,\tau}] \times (1 - \hat{s}_{t+1}) \\ & + [\alpha_{i,1} + \beta_{i,1}B(L^{1/m}; \boldsymbol{\theta}_{i,1})CS_t + \rho_{i,1}REV_{i,t,\tau}] \times \hat{s}_{t+1} + \varepsilon_{i,t+1}, \end{aligned} \quad (4.7)$$

where \hat{s}_{t+1} is a dummy variable assorted by the ADS index defining economic states between t and $t + 1$.

The second and the third row in Figure (4-9) illustrate the histogram of the estimates of (β_i) and ρ_i in good and bad economic states. In both states, a majority of forecasters revises output forecasts downwards when credit spread increases but has substantial rigidities updating forecasts as shown in positive $\hat{\rho}_i$ s. However, estimates of the both coefficients are more dispersed in bad state, showing that forecasters disagree more in bad state as responding to high-frequency financial information than in good state when they show more concentrated distributions. This result suggests that the information from the market forecasters are more dispersed in troubled times, so policy makers such as monetary authorities should pay much attention to the signal from the financial markets.

As shown in this exercise, forecasters' behaviour incorporating high-frequency financial information differ substantially. In order to find a possible link between the individuals' revising behaviour using financial information and their forecasting ability, we initiate a simple regression connecting the individual forecasters' abilities and the degree of responses to daily credit spreads. Individuals' forecasting abilities are measured using the root mean squared forecast errors (Deschamps and Ioannidis 2013) over the entire period (1991-2016), defined as $RMSE_i = [(1/(26 \times 24))\sum_{\tau=1991}^{2016}\sum_{h=1}^{24}e_{i,\tau,h}^2]^{1/2}$,²⁵ where $e_{i,\tau,h}^2$ is the squared forecast errors for forecast i . Evaluating forecast errors, we use data of the first release as

standard in the literature (Dovern and Weisser 2011; Chen et al. 2016; El-Shagi et al. 2016).²⁶

We expect that a forecaster who incorporates financial information strongly and consistently with their empirical reality will show higher overall ability. In specific, we estimate the relationship between individual *RMSEs* and estimated slope coefficients on the daily credit spread ($\hat{\beta}_i$) using simple regression:

$$RMSE_i = \delta_0 + \delta_1 \hat{\beta}_i + \varepsilon_i. \quad (4.8)$$

Figure (4-10) plots the relationship between the two variables. As *RMSE* increases with higher forecast errors on average, lower *RMSE* indicates higher ability. The coefficients on credit spreads ($\hat{\beta}_i$) are positively related with $RMSE_i$, but only the relationship is statistically significant when the economy is in bad states. We report the estimation results in Table (4.3), confirming that $\hat{\delta}_1$ is positive and significant at 5% level in bad state. This result implies that responding more actively and consistently to the developments in credit market conditions enables forecasters to make smaller forecasting errors on average, but this relationship is mostly dependent upon their strong responses during bad economic states.

²⁵Using mean squared errors (MSE) instead of RMSE measuring forecasters' abilities gives similar results.

²⁶The real-time macroeconomic data set of diverse vintages are provided by the Federal Reserve Bank of Philadelphia at <https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data>.

4.5 Conclusion

This paper has explored the relationship between high-frequency financial information and forecast revisions. Using a Mixed Data Sampling (MIDAS) regression approach, we have provided empirical evidence that daily changes in credit spreads have a significant predictive ability for monthly forecast revisions for GDP growth. Specifically, we have shown that increases in daily credit spreads, measured as the difference between long-term Aaa-rated corporate bonds and the constant maturity 10-year Treasury, significantly forecast downward revisions on average and also at the individual forecast level.

The weighting functions of all the four MIDAS regressions we examined have indicated hump-shaped polynomials, suggesting that forecasters do not respond in a sufficient and timely manner incorporating all high-frequency information in financial markets. Testing the difference of the effect between economic states, we show that the effect of credit spreads on GDP forecast revisions is more prominent when the economy is in bad states, consistently with the previous literature studying state-dependent expectations formations in survey forecasts.

Table 4.1: Parameter Estimates for MIDAS Regressions

	α	β	θ_1	θ_2	ρ	R^2
<i>M1</i>	-0.007 (-0.660)	-9.948 (-6.505)	3.026 (2.363)	1.824 (3.673)	0.503 (11.173)	0.392
	α	θ_1	θ_2	θ_3	ρ	R^2
<i>M2</i>	-0.009 (-0.833)	0.288 (1.042)	-0.192 (-3.308)	0.008 (3.232)	0.507 (11.095)	0.377
	α				ρ	R^2
<i>M0</i>	-0.008 (-0.781)				0.516 (7.960)	0.261

Notes: This table reports the coefficient estimates in MIDAS regression of the revisions of consensus GDP growth rates on a lag of revisions and changes on credit spreads (the difference between Aaa-rated corporate bond and 10-year Treasury rates). α is a constant, β is a slope coefficient in model M1 on high-frequency (daily) Aaa-spread, and ρ is a coefficient on the lag of revisions. θ 's are the parameters determining the shape of weighting polynomials on the daily credit spreads. M0 is a model without daily credit spreads. See equations (4.1) and (4.2) for further details. The values in parentheses are t-statistics. The sample period covers from 1991 to 2016.

Table 4.2: Parameter Estimates for MIDAS Regressions in Good and Bad Economic States

<i>Panel A. Good States</i>						
	α_0	β_0	$\theta_{0,1}$	$\theta_{0,2}$	ρ_0	R^2
<i>M1</i>	0.020 (1.950)	-6.028 (-3.635)	1.795 (2.242)	1.025 (24.491)	0.461 (7.783)	0.268
	α_0	$\theta_{0,1}$	$\theta_{0,2}$	$\theta_{0,3}$	ρ_0	R^2
<i>M2</i>	0.020 (1.945)	-0.319 (-1.002)	0.018 (0.265)	-0.001 (-0.441)	0.469 (7.887)	0.270
	α_0				ρ_0	R^2
<i>M0</i>	0.018 (1.685)				0.473 (6.903)	0.228
<i>Panel B. Bad States</i>						
	α_1	β_1	$\theta_{1,1}$	$\theta_{1,2}$	ρ_1	R^2
<i>M1</i>	-0.054 (-2.430)	-13.530 (-5.245)	3.432 (2.170)	2.186 (3.257)	0.472 (6.244)	0.446
	α_1 <td>$\theta_{1,1}$<td>$\theta_{1,2}$<td>$\theta_{1,3}$<td>ρ_1<td>R^2</td></td></td></td></td>	$\theta_{1,1}$ <td>$\theta_{1,2}$<td>$\theta_{1,3}$<td>ρ_1<td>R^2</td></td></td></td>	$\theta_{1,2}$ <td>$\theta_{1,3}$<td>ρ_1<td>R^2</td></td></td>	$\theta_{1,3}$ <td>ρ_1<td>R^2</td></td>	ρ_1 <td>R^2</td>	R^2
<i>M2</i>	-0.060 (-2.602)	0.952 (2.004)	-0.403 (-4.041)	0.018 (4.027)	0.492 (6.296)	0.430
	α_1 <td colspan="3"></td> <td>ρ_1<td>R^2</td></td>				ρ_1 <td>R^2</td>	R^2
<i>M0</i>	-0.074 (-2.169)				0.442 (4.342)	0.175

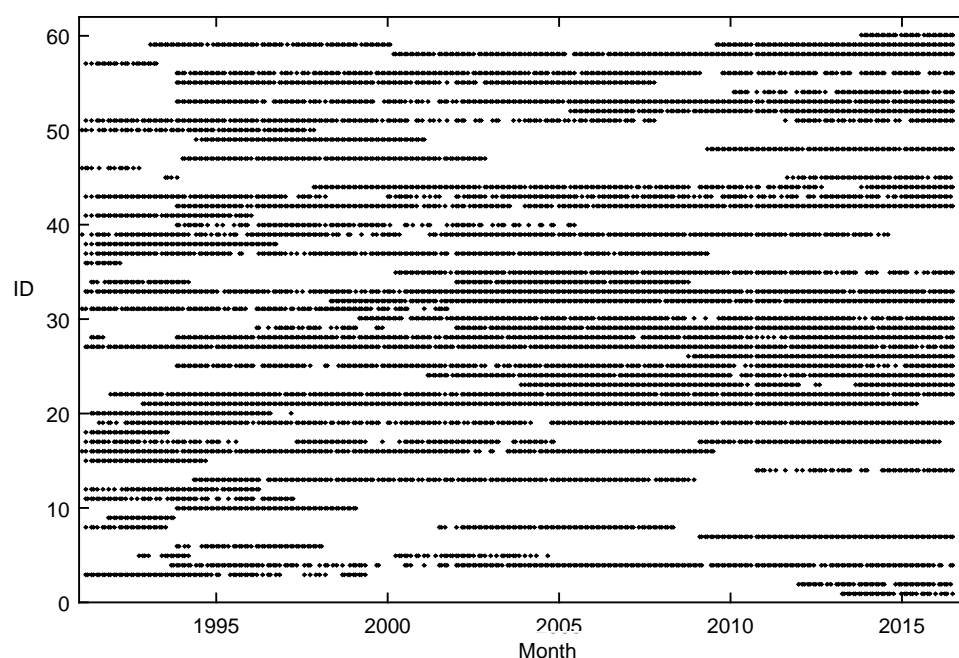
Notes: This table reports the coefficient estimates in MIDAS regression of the revisions of consensus GDP growth rates on a lag of revisions and changes on credit spreads (the difference between Aaa-rated corporate bond and 10-year Treasury rates). α is a constant, β is a slope coefficient in model M1 on high-frequency (daily) Aaa-spread, and ρ is a coefficient on the lag of revisions. θ 's are the parameters determining the shape of weighting polynomials on the daily credit spreads. M0 is a model without daily credit spreads. See equations (4.2), (4.3), and (4.5) for further details. The values in parentheses are t-statistics. The sample period covers from 1991 to 2016.

Table 4.3: Responses to Credit Spread and Forecasting Abilities

	δ_0	δ_1	R^2	N
<i>All States</i>	0.563 (37.298)	0.001 (0.577)	0.008	41
<i>Good States</i>	0.557 (39.095)	0.000 (0.110)	0.000	41
<i>Bad States</i>	0.571 (50.528)	0.002 (2.186)	0.109	41

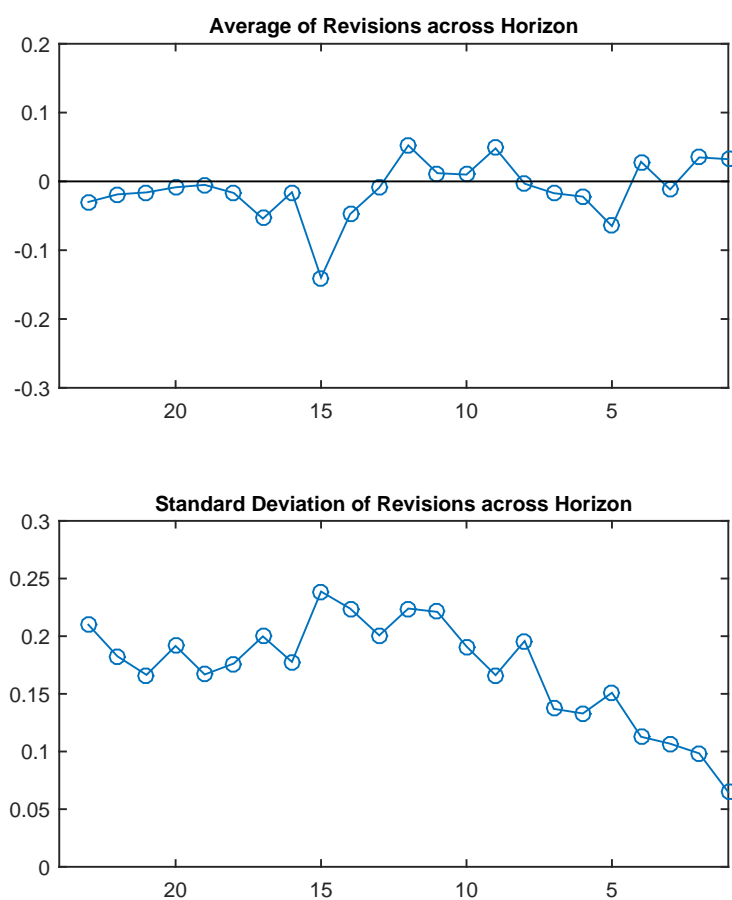
Notes: This table reports the estimates in a simple regression testing the relationship between the degree of responses to daily credit spreads ($\hat{\beta}_i$ in the model M1) and individual forecasting ability (see Equation (4.8)) across economic states. Individuals' forecasting abilities are measured by the root mean squared forecast errors. The values in parentheses are Newey-West t-statistics (Newey and West 1987). The sample period covers from 1991 to 2016.

Figure 4-1: Survey Participation



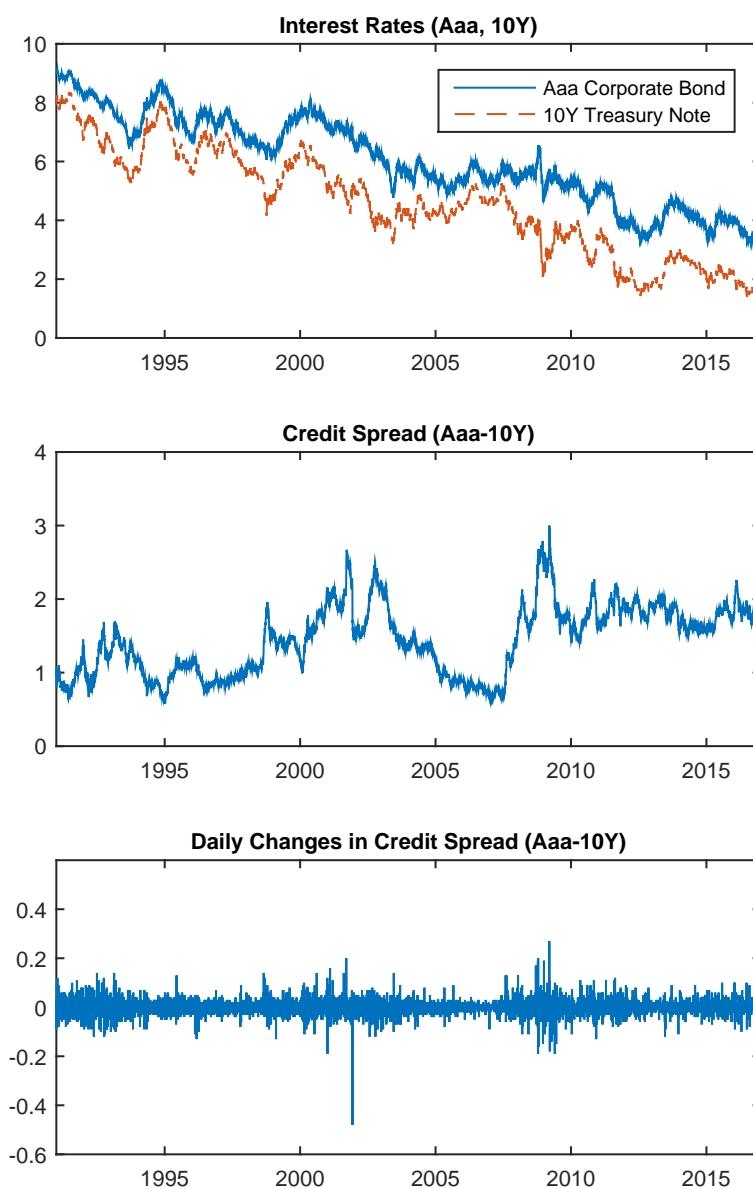
Notes: The figure illustrates the participation of the survey panellists forecasting GDP Growth. X-axis denotes sample period from January 1991 to December 2016 and Y-axis are the ids of forecasters (60 in total).

Figure 4-2: Mean and Standard Deviation of Revisions



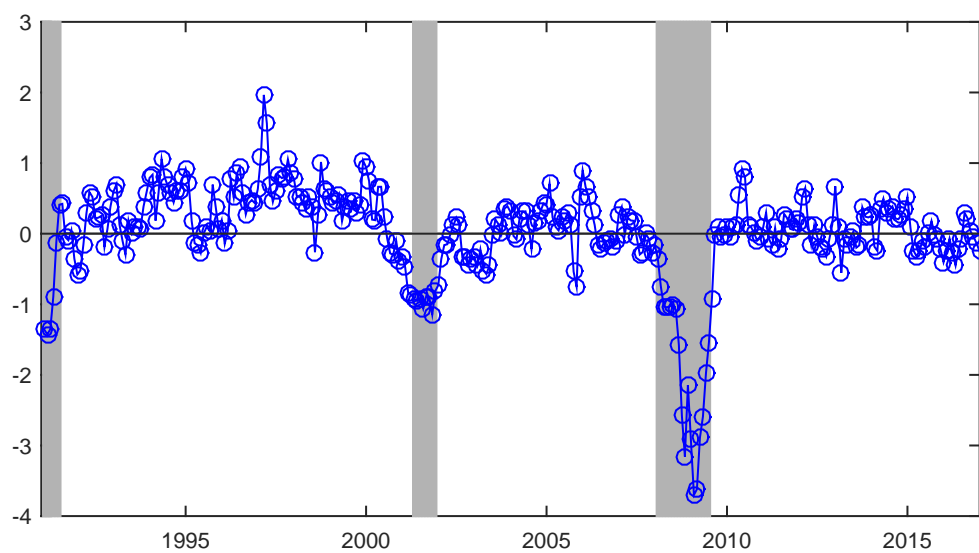
Notes: The figure illustrates the means and standard deviations of individual (60 in total) forecasts revisions across revision horizons ($h = 23, 22, \dots, 1$). X axis denotes revision horizons. Sample period is from January 1991 to December 2016.

Figure 4-3: Interest Rates and Spread



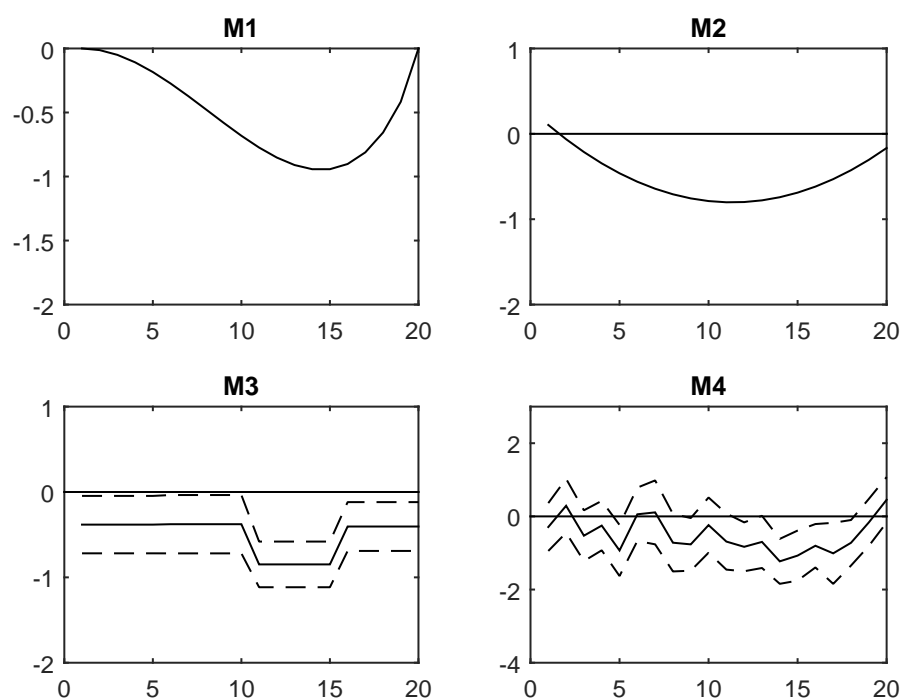
Notes: The plot at top of the page row plots daily interest rates for Aaa-rated corporate bond and 10-year Treasury Note between 1991 and 2016. The second plot show Aaa-spread measured as the difference between the two rates. The plot at the bottom plots daily changes of Aaa-spreads.

Figure 4-4: ADS Index



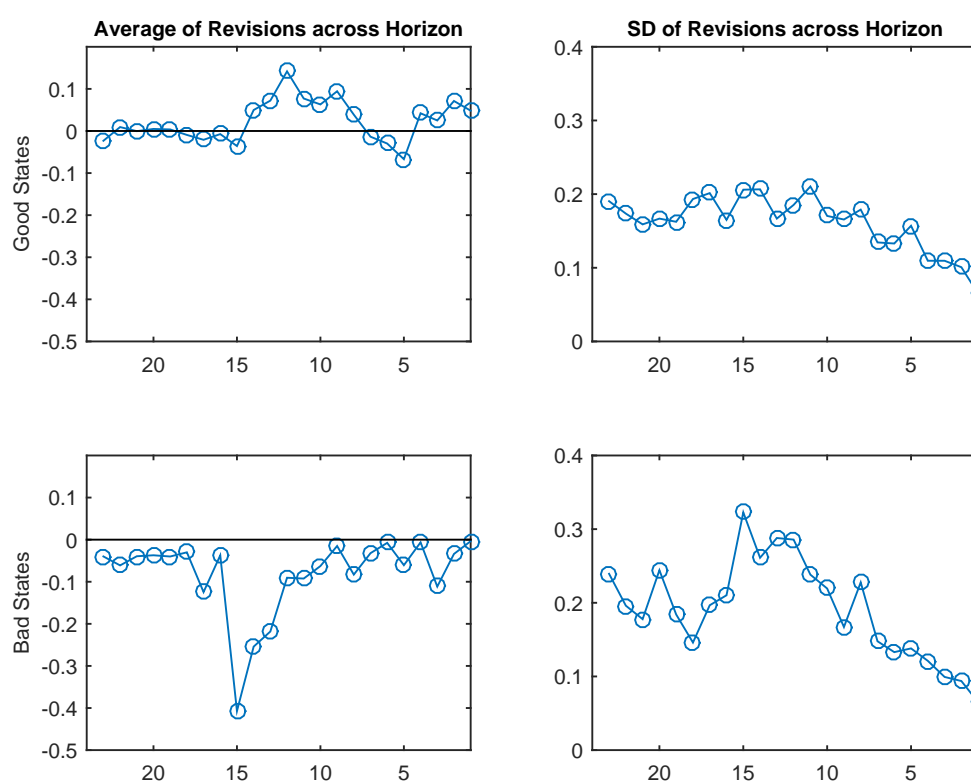
Notes: This figure plots the real-time measure of business conditions developed by Aruoba, Diebold, and Scotti (2009). The original daily series is matched to monthly forecasting cycles by averaging daily index between the previous and current survey deadlines. The shaded areas denote the recessions defined by National Bureau of Economic Research (NBER). Sample period covers from 1991 to 2016.

Figure 4-5: MIDAS Coefficients in All Economic States



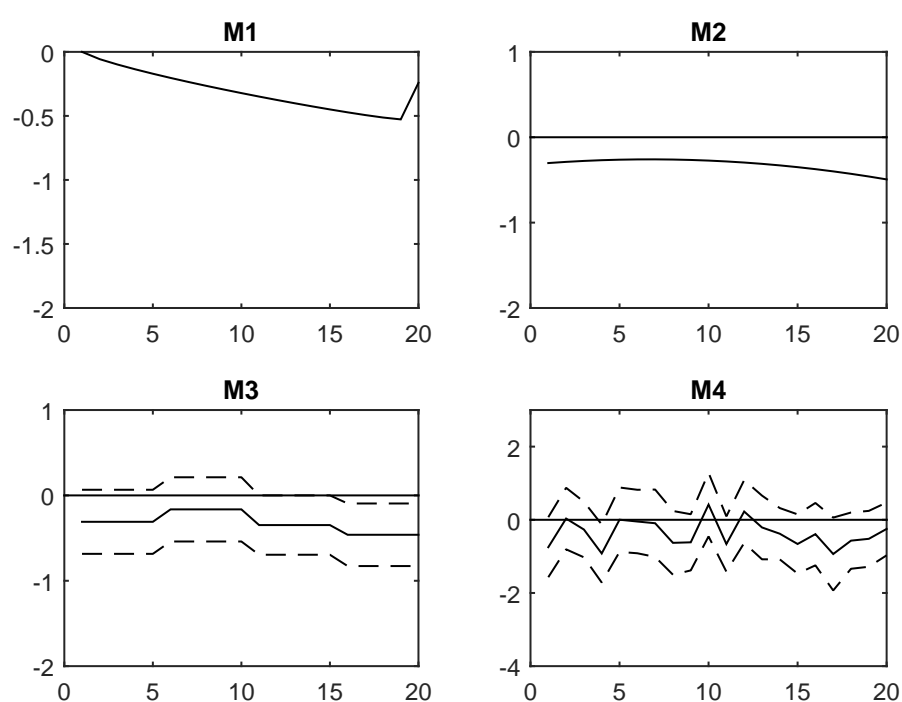
Notes: This figure plots the estimated MIDAS coefficients for the four weighting functions. Estimations are based on normalised beta probability density function (M1), Almon lag polynomials (M2), Step-weighting function (M3), and U-MIDAS (M4). The dashed lines in M3 and M4 indicate two standard errors from the estimates.

Figure 4-6: Mean and Standard Deviation of Revisions



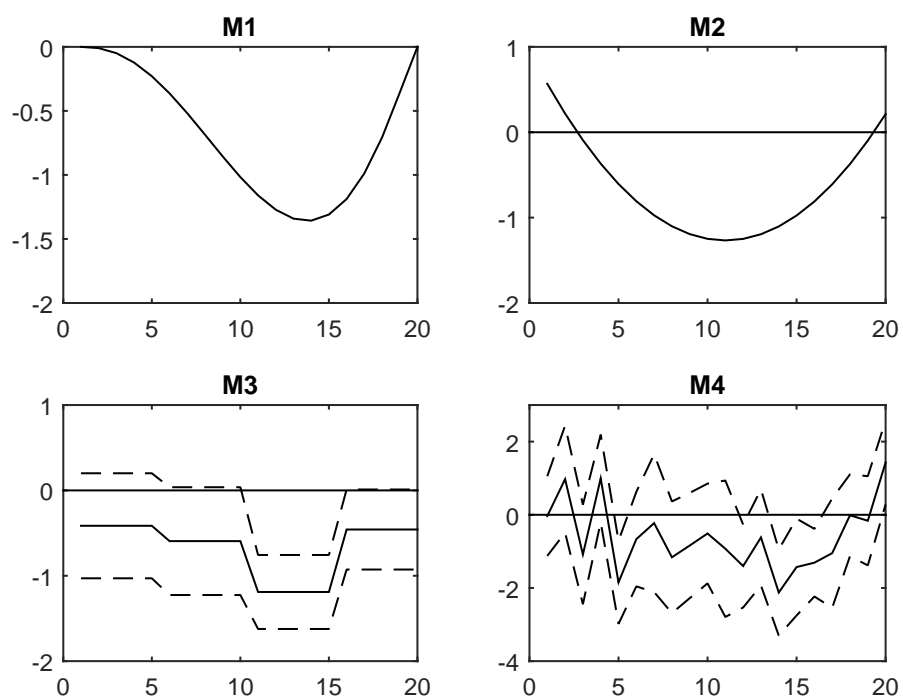
Notes: The figure illustrates the means and standard deviations of individual (60 in total) forecasts revisions across revision horizons ($h = 23, 22, \dots, 1$) and economic states (good and bad states). Economic states are identified by averaging daily ADS (Aruoba-Diebold-Scotti) index matched to monthly survey cycles. X axis denotes revision horizons. Sample period is from January 1991 to December 2016.

Figure 4-7: MIDAS Coefficients in Good Economic State



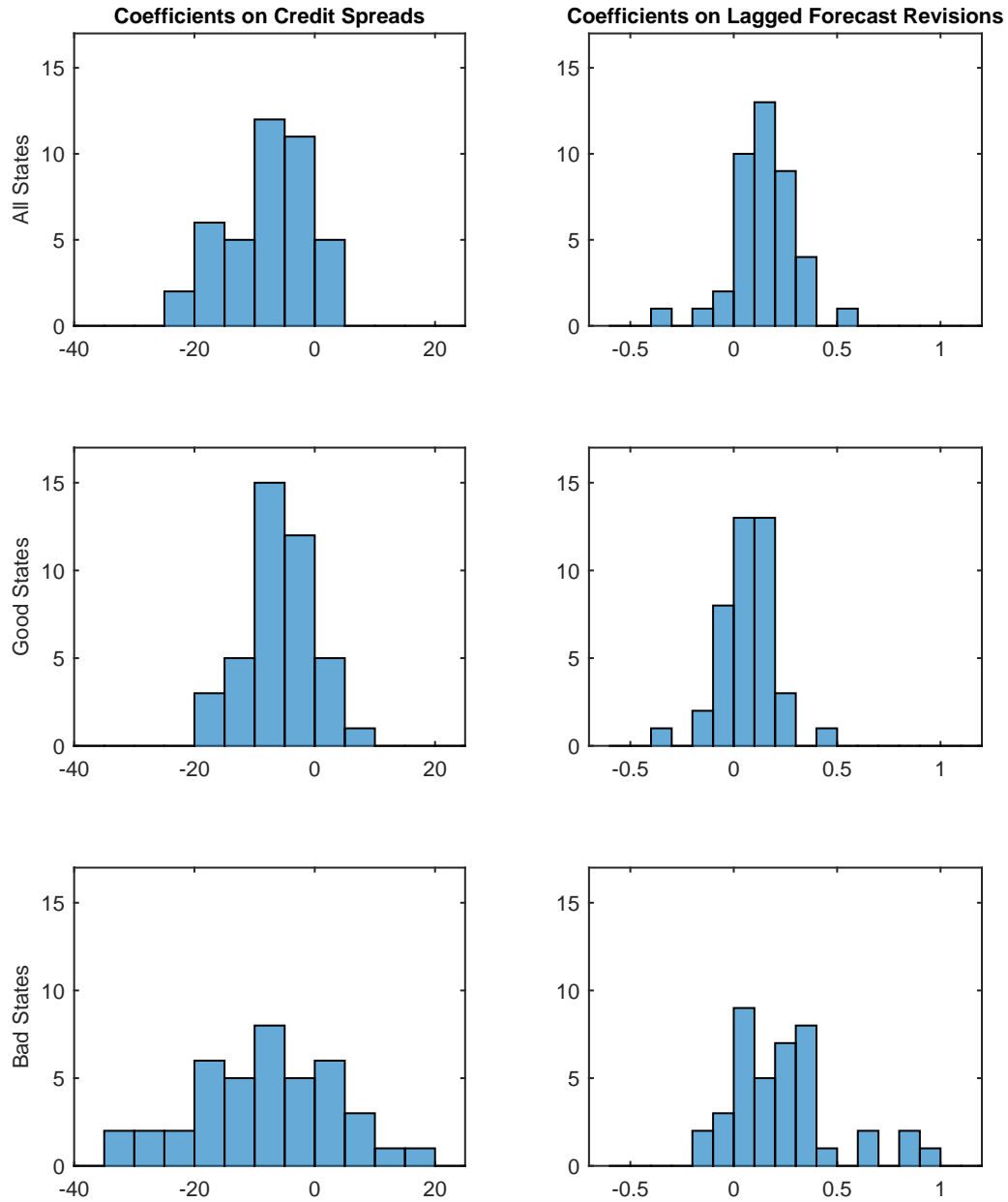
Notes: This figure plots the estimated MIDAS coefficients for the four weighting functions with only good economic states. Economic states are identified by averaging daily ADS (Aruoba-Diebold-Scotti) index matched to monthly survey cycles. The estimates are based on normalised beta probability density function (M1), Almon lag polynomials (M2), Step-weighting function (M3), and U-MIDAS (M4). The dashed lines in M3 and M4 indicate two standard errors from the estimates.

Figure 4-8: MIDAS Coefficients in Bad Economic State



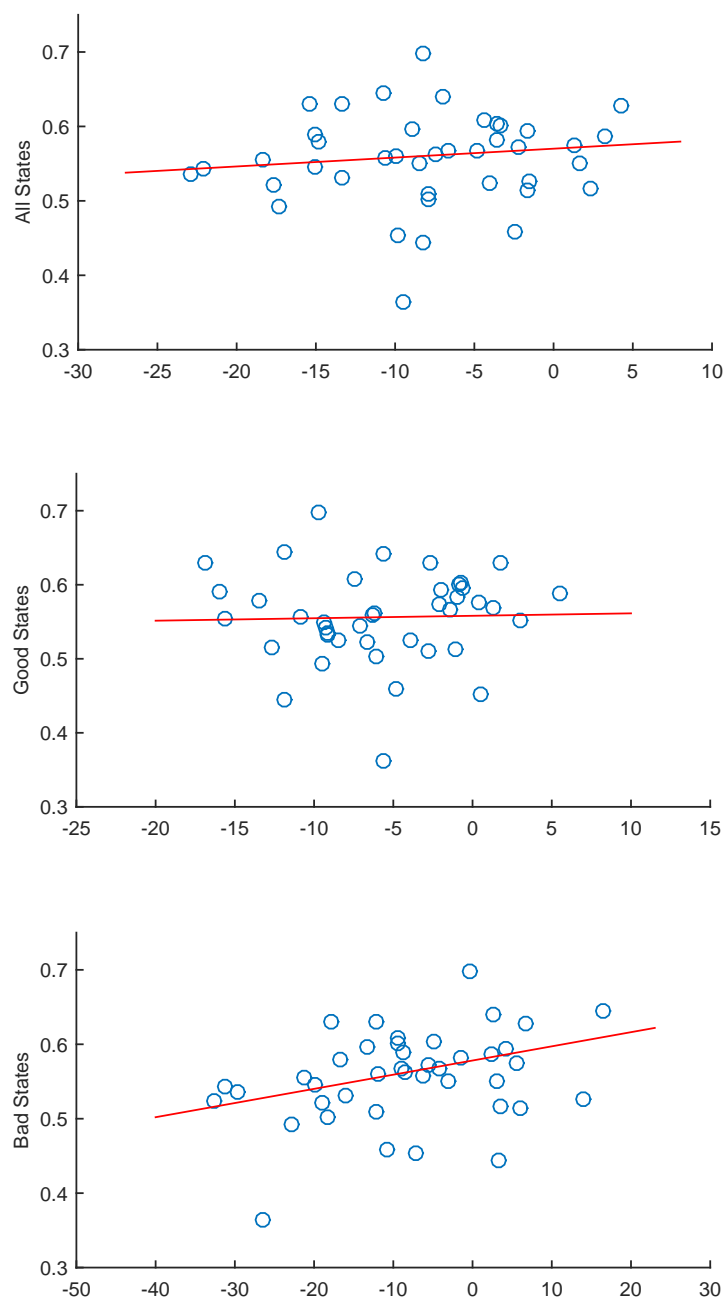
Notes: This figure plots the estimated MIDAS coefficients for the four weighting functions with only bad economic states. Economic states are identified by averaging daily ADS (Aruoba-Diebold-Scotti) index matched to monthly survey cycles. The estimates are based on normalised beta probability density function (M1), Almon lag polynomials (M2), Step-weighting function (M3), and U-MIDAS (M4). The dashed lines in M3 and M4 indicate two standard errors from the estimates.

Figure 4-9: MIDAS Coefficients at the Individual Level



Notes: This figure plots histograms of slope coefficients (β_i) on credit spreads and on lagged forecast revisions (ρ_i) across economic states, estimated using MIDAS regressions M1 (based on normalised beta probability density function). Forecasters with less than 50 revisions are excluded, leaving 41 forecasters in total.

Figure 4-10: Individual MIDAS Coefficients and Forecasting Abilities



Notes: This figure plots the relationship between the slope coefficients (β_i) on credit spreads across economic states estimated using M1 and individuals' forecasting ability measured by the root mean squared forecast errors. Forecasters with less than 50 revisions are excluded, leaving 41 forecasters in total.

Matlab codes for Chapter 4

The following codes require MIDAS Matlab Toolbox (version 2.2) for running. The toolbox is available from mathworks.com.

(1) Consensus Forecast Revisions

```
[DataYt,DataYdate] = xlsread('data_rev.xlsx','rev');
DataYdate = DataYdate(2:end,1);
DataYM = DataYt(:,1);
ExoRegM = DataYt(:,2);
ExoRegDate = DataYdate;

[DataXt,DataXdate] = xlsread('data_rev.xlsx','spread');
DataX3 = [DataXt(:,3)]; % CB(Aaa)-T10y Spread
DataX = DataX3;
DataXdate = DataXdate(2:end,1);
DataY = DataYM; ExoReg = ExoRegM;

%% Build Data for Good or Bad time
realact = DataYt(:,3);
load('states_dummy.mat');
DataY_realact_h = NaN(size(dummy,1),1);
DataY_realact_l = NaN(size(dummy,1),1);
realact_dum = NaN(size(DataYC,1),1);

for k=1:size(realact)
    cut=quantile(realact,1/3);
    if realact(k,1)>=cut
        realact_dum(k,1)=1;
    else
        realact_dum(k,1)=0;
    end
end
for l=1:size(dummy,1)
    if realact_dum(l,1)==1
        DataY_realact_h(l,1)=DataY(l,1);
    else
        DataY_realact_l(l,1)=DataY(l,1);
    end
end

%% Select Good or Bad States
%DataY = DataY_realact_h;
%DataY = DataY_realact_l;

%% Build the Changes of the spread (Daily Change)
datasize=size(DataX,1);
```

```

DataXd=[NaN(datasize,1)];
for i=3:datasize
    if isnan(DataX(i,1))==1
        DataXd(i,1)=NaN(1,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-2,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==1 && isnan(DataX(i-3,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-3,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==1 && isnan(DataX(i-3,1))==1 && isnan(DataX(i-4,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-4,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==1 && isnan(DataX(i-3,1))==1 && isnan(DataX(i-4,1))==1 && isnan(DataX(i-5,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-5,1);
    else
        DataXd(i,1)=DataX(i,1)-DataX(i-1,1);
    end
end
DataX = DataXd;

%% Specify lag structure and sample size
Xlag = 20;
Ylag = 0;
Horizon = 3;

%% Select Estimation Sample
EstStart = '1991-02-01';
EstEnd = '2016-12-01';
Method = 'fixedWindow';

[OutputForecast1,OutputEstimate1,MixedFreqData,ExtendedForecast] =
MIDAS_ADL(DataY,DataYdate,DataX,DataXdate,...

'Xlag',Xlag,'Ylag',Ylag,'Horizon',Horizon,'EstStart',EstStart,'EstEnd',EstEnd
,'ExoReg',ExoReg,'ExoRegDate',ExoRegDate,'Polynomial','beta','Method',Method)
;
[OutputForecast2,OutputEstimate2] =
MIDAS_ADL(DataY,DataYdate,DataX,DataXdate,...

'almonDegree',2,'Xlag',Xlag,'Ylag',Ylag,'Horizon',Horizon,'EstStart',EstStart
,'EstEnd',EstEnd,'ExoReg',ExoReg,'ExoRegDate',ExoRegDate,'Polynomial','Almon'
,'Method',Method,'Display','estimate');
[OutputForecast3,OutputEstimate3] =
MIDAS_ADL(DataY,DataYdate,DataX,DataXdate,...

'Xlag',Xlag,'Ylag',Ylag,'Horizon',Horizon,'EstStart',EstStart,'EstEnd',EstEnd

```



```

, 'ExoReg', ExoReg, 'ExoRegDate', ExoRegDate, 'Polynomial', 'step', 'Method', Method,
'Display', 'estimate');
[OutputForecast4, OutputEstimate4] =
MIDAS_ADL(DataY, DataYdate, DataX, DataXdate, ...

'Xlag', Xlag, 'Ylag', Ylag, 'Horizon', Horizon, 'EstStart', EstStart, 'EstEnd', EstEnd
, 'ExoReg', ExoReg, 'ExoRegDate', ExoRegDate, 'Polynomial', 'umidas', 'Method', Metho
d, 'Display', 'estimate');

fprintf('RMSE Beta:           %5.4f\n', OutputForecast1.RMSE);
fprintf('RMSE Almon:         %5.4f\n', OutputForecast2.RMSE);
fprintf('RMSE Stepfun:       %5.4f\n', OutputForecast3.RMSE);
fprintf('RMSE U-MIDAS:       %5.4f\n', OutputForecast4.RMSE);
disp(' ')

Xlag = MixedFreqData.Xlag;
nModel = 4;
nrow = ceil(sqrt(nModel));
ncol = ceil(nModel./nrow);
weightsall=[];
for m = 1:nModel
    weights = eval(['OutputEstimate', num2str(m), '.estWeights']);
    subplot(nrow, ncol, m); plot(1:Xlag, weights);
    title(eval(['OutputEstimate', num2str(m), '.model(7:end)']));
    weightsall=[weightsall weights];
end

%% Regression with only Lags
ExoReg2 = ExoReg(~isnan(DataY)); ExoReg2=ExoReg2(2:end, :);
DataY2=MixedFreqData.EstY(~isnan(ExoReg2)); ExoReg2=ExoReg2(~isnan(ExoReg2));
[Coefficients, Estimates, Residuals, R2, stats] =
regression(DataY2, ExoReg2, 0.05, 1);

%% Generate a plot of weights
Xlag = MixedFreqData.Xlag;
nModel = 4;
nrow = 2;
ncol = 2;
figure
weights = zeros(Xlag, nModel);
for m = 1:nModel
    weights(:, m) = eval(['OutputEstimate', num2str(m), '.estWeights']);
end
error5= eval(['OutputEstimate', num2str(5), '.se']); error5=error5(2:end-
1,:); error5=[error5 error5 error5 error5 error5]';
error5=error5(:)*2;
error4= eval(['OutputEstimate', num2str(4), '.se']); error4=error4(2:end-
1,:)*2;
zerol = zeros(21, 1);

```

```

subplot(nrow,ncol,1);plot(1:Xlag,weights(:,1),'-k');
axis([0 20 -2 0])
title('M1')
subplot(nrow,ncol,2);plot(1:Xlag,weights(:,2),'-k',0:Xlag,zerol,'-k');
axis([0 20 -2 1])
title('M2')
subplot(nrow,ncol,3);plot(1:Xlag,weights(:,3),'-k',1:Xlag,weights(:,3)-
serror5,'--k',1:Xlag,weights(:,3)+serror5,'--k',0:Xlag,zerol,'-k');
axis([0 20 -2 1])
title('M3')
subplot(nrow,ncol,4);plot(1:Xlag,weights(:,4),'-k',1:Xlag,weights(:,4)-
serror4,'--k',1:Xlag,weights(:,4)+serror4,'--k',0:Xlag,zerol,'-k');
axis([0 20 -4 3])
title('M4')

```

(2) Individual Forecast Revisions

```

[DataYt,DataYdate] = xlsread('data_rev.xlsx','rev');
DataYdate = DataYdate(2:end,1);

DataYM = DataYt(:,1);
ExoRegM = DataYt(:,2);

load('revid_test_m.mat'); DataYid = revid_test_m;
load('revnum_m.mat'); revnum=revnum_m; DataYdate=DataYdate(1:end-6,:);
ExoRegDate=DataYdate;

%% Select High-Freq(daily) Financial Variable
[DataXt,DataXdate] = xlsread('data_rev_us.xlsx','spread');
DataX3 = [DataXt(:,3)]; % CB(Aaa)-T10y Spread

%% Select High Frequency Data
DataX = DataX3;
DataY = DataYM; ExoReg = ExoRegM;
DataXdate = DataXdate(2:end,1);

%% Test between Good or Bad time
realact = DataYt(:,20);
load('states_dummy.mat');
DataYid_realact_h = NaN(size(dummy,1),5,60);
DataYid_realact_l = NaN(size(dummy,1),5,60);
realact_dum = NaN(size(DataYC,1),1);

for id=1:60
for k=1:size(realact)
    if realact(k,1)>quantile(realact,1/3)

```

```

        realact_dum(k,1)=1;
    else
        realact_dum(k,1)=0;
    end
end
for l=1:size(dummy,1)
    if realact_dum(l,1)==1
        DataYid_realact_h(l,:,id)=DataYid(l,:,id);
    else
        DataYid_realact_l(l,:,id)=DataYid(l,:,id);
    end
end
end

%% Select Good or Bad States
%DataYid = DataYid_realact_h;
%DataYid = DataYid_realact_l;

%% Build the Changes of the spread (Daily Change)
datasize=size(DataX,1);
DataXd=[NaN(datasize,1)];
for i=3:datasize
    if isnan(DataX(i,1))==1
        DataXd(i,1)=NaN(1,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-2,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==1 && isnan(DataX(i-3,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-3,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==1 && isnan(DataX(i-3,1))==1 && isnan(DataX(i-4,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-4,1);
    elseif isnan(DataX(i,1))==0 && isnan(DataX(i-1,1))==1 && isnan(DataX(i-2,1))==1 && isnan(DataX(i-3,1))==1 && isnan(DataX(i-4,1))==1 && isnan(DataX(i-5,1))==0
        DataXd(i,1)=DataX(i,1)-DataX(i-5,1);
    else
        DataXd(i,1)=DataX(i,1)-DataX(i-1,1);
    end
end

DataX = DataXd;

Coefficientsall=[]; stats =[]; R2all=[]; statsall=[]; Rmseall=[];
weightsall1=[]; weightsall5=[]; weightsall6=[]; rsquareall1=[];
rsquareall5=[]; rmseall1=[];
betas1_id = NaN(size(revnum,1),6);
for id = 1:size(revnum,1)

```

```

        if revnum(id,1)>=50

DataYsid = DataYid(:,4,id); ExoRegsid = DataYid(:,5,id);
DataY = DataYsid; ExoReg = ExoRegsid;
Xlag = 20;
Ylag = 0;
Horizon = 3;
EstStart = '1991-02-01';
EstEnd = '2016-12-01';
Method = 'fixedWindow';

[OutputForecast1,OutputEstimate1,MixedFreqData,ExtendedForecast] =
MIDAS_ADL(DataY,DataYdate,DataX,DataXdate,...

'Xlag',Xlag,'Ylag',Ylag,'Horizon',Horizon,'EstStart',EstStart,'EstEnd',EstEnd
,'ExoReg',ExoReg,'ExoRegDate',ExoRegDate,'Polynomial','beta','Method',Method)
;

fprintf('RMSE Beta:           %5.4f\n',OutputForecast1.RMSE);
disp(' ')

% Generate a plot of weights
Xlag = MixedFreqData.Xlag;
nModel = 6;
nrow = ceil(sqrt(nModel));
ncol = ceil(nModel./nrow);
m = 1;
    weights = eval(['OutputEstimate',num2str(m),'.estWeights']);
    rsquare = eval(['OutputEstimate',num2str(m),'.r2']);

% Generate a plot of weights
Xlag = MixedFreqData.Xlag;
nModel = 1;
nrow = ceil(sqrt(nModel));
ncol = ceil(nModel./nrow);

weights1 = eval(['OutputEstimate',num2str(1),'.estWeights']);
rsquare1 = eval(['OutputEstimate',num2str(1),'.r2']);
resid1 = eval(['OutputEstimate',num2str(1),'.resid']);
weightsall1=[weightsall1 weights1];
rsquareall1 = [rsquareall1 rsquare1];
rmseall1 = [rmseall1; (resid1'*resid1/size(resid1,1))^0.5];

betas1_id(id,:) = [id revnum(id,1) OutputEstimate1.estParams(2,1)
OutputEstimate1.tstat(2,1) OutputEstimate1.estParams(5,1)
OutputEstimate1.tstat(5,1)];
    else
        betas1_id(id,:) = [id revnum(id,1) NaN(1,4)];

```

```

        weightsall1=[weightsall1 NaN(20,1)];
    end
end

%% Histogram
betas1_id_hist=[];
for id=1:60
    if betas1_id(id,2)>=50
        betas1_id_hist=[betas1_id_hist; betas1_id(id,:)];
    end
end
figure
subplot(1,2,1)
histogram(betas1_id_hist(:,3), [-40:5:25])
axis([-40 25 0 17])
ylabel('Bad States')
subplot(1,2,2)
histogram(betas1_id_hist(:,5), [-0.6:0.1:1.2])
axis([-0.7 1.2 0 17])

%% Size of Beta and Forecasting Ability (RMSE)
rmseid_ab=rmseid(betas1_id(:,2)>=50,2);
betas1_id_ab=betas1_id(betas1_id(:,2)>=50,3);
ab=[rmseid_ab betas1_id_ab];
[Coefficients_ab, Estimates_ab, Residuals_ab, R2_ab, stats_ab] =
regression(rmseid_ab,betas1_id_ab,0.05,1);
figure;
scatter(ab(:,2),ab(:,1))
axis([-50 30 0.30 0.75])
ylabel('All States')
hold on;
    coef_fit = polyfit(betas1_id_ab,rmseid_ab,1);
    y_fit = polyval(coef_fit, [-40 30]);
    plot([-40 23],y_fit,'r');
hold off;

```

Chapter 5

Conclusion

In this thesis, we have explored the relationships between the macroeconomy and the term structure of interest rates in a macro-finance perspective. The focus has been placed on studying how macroeconomic shocks originating from home and abroad affect price formation in bond markets as well as how information in financial markets is incorporated in macroeconomic forecasts.

The first two chapters focus on the former question investigating the effects of macroeconomic shocks on the term structure of interest rates by influencing economic agents' expectations over future economic developments. In the first chapter, we have examined the impact of oil price shocks in the global crude oil markets on the dynamics of the term structure in four economies; the US, Canada, Norway, and South Korea. The selected industrialised countries, all are open economies with flexible exchange rates differing in their dependence on oil. Two are net importers and two are net exporters. The responses of the yield factors (level, slope, and curvature) to oil market shocks are shown to differ contingent on the underlying sources of the driving oil price shocks and the different dependencies

on energy across the countries. These are found to deliver different responses of the yield factors. More specifically, oil market-specific demand shocks, related to the precautionary oil demand, increase the level of the yield curves in oil importing countries, but have limited effects in oil exporting countries. Oil supply shocks induce temporary decrease of the slope factors in the US and Canada, whilst aggregate demand shocks lead to increases in the slopes in all countries, of which responses are related to monetary policy responses cushioning the impact of oil price shocks.

In the second chapter, we sought to identify economically meaningful variables to account for the fluctuations in the unobserved term premia of long term bonds during the business cycle. We have investigated the predictive ability of economic policy uncertainty (EPU) for future bond returns. The effects of EPU on bond excess returns are shown to be significantly positive for shorter maturities in near investment horizons. Our five-factor affine term structure model incorporating EPU and Cochrane and Piazzesi (2005)'s return forecasting factor, replacing the fourth and fifth yield factors extracted from contemporaneous yields with diverse maturities, produces time-varying and countercyclical term premia estimates. The model-implied term premia on medium- and long-term rates provide the explanation for additional compensation, demanded in times of heightened economic uncertainty. These fluctuations in term premia due to EPU suggest a risk-pricing channel via which policy uncertainty propagates to macroeconomic variables, such as investment and employment.

The third chapter has studied another aspect of the macro-finance relationship by examining the information content of high-frequency asset prices in forecasting macroeconomic variables. Using Mixed Data Sampling (MIDAS) regressions connecting high-frequency financial asset prices with low-frequency survey forecasts,

we have shown that daily changes in credit spread are able to predict forecast revisions for output growth rate. The credit spread, the difference between the yield of the corporate Aaa-rated bond and the equivalent maturity Treasury, serves as an indicator for, in the first instance, corporate risk of default and future conditions of credit tightening reflecting expectations of future macroeconomic conditions. The relations are found to exist at both aggregate (consensus) and individual level forecasts. Testing the relations in different economic states, we have found that credit conditions affect forecast revisions, prominently during ‘bad’ economic conditions. This finding is consistent with the predictions of macroeconomic models incorporating the financial accelerator.

All in all, the three essays in this thesis suggest that the dynamics of the term structure of interest rates are closely related to macroeconomic conditions and the information embedded in the prices of these financial assets can be used for forecasting macroeconomic variables as it represents economic agents’ expectations over future economic developments.

Our study leaves several possible directions for future research. The model in the first essay focuses on specific effects of oil prices shocks considering different oil shocks and countries, but the model does not explicitly include important macroeconomic channels such as monetary policy and exchange rates. An analytical framework accommodating both oil-importing and oil-exporting countries could lead to a more general understanding of these relations, enriching our empirical results.

Secondly, the exercise finding relationship between financial asset prices and the survey forecasts could be extended by using alternative variables as well as by using countries other than the US. Testing the effects of other relevant high-

frequency financial series such as VIX, CDX spread and the slope of the yield curve would lead to further benefits from the perspective of forecasting.

Finally, the inclusion of EPU was proven to provide the pricing equation for long-term bonds with an economic explanation regarding the evolution of the premia, independently of the shape and position of the yield curve. The study can be enriched by testing for its relevance to other bond markets in the US and other countries as the availability of this index has become widespread. Furthermore, the simultaneous estimation of the yield curves of major trading blocks, for example the USA and Japan, in the presence of their individual EPU shocks will provide for a more rounded view of the determination of term-premia in an international context. We leave these investigations for future research.

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